Auction Design and the Incentives to Invest: Evidence from Procurement Auctions*

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Abstract

While there is a growing theoretical literature that analyzes pre-auction investment, much of the empirical literature has focused on allocative efficiency or revenue maximization in static settings. This paper studies auction design when the seller can make costly investments to improve the quality of the good, using data from municipal plastic recycling auctions in Japan. We estimate the bidders' valuation for quality –cleanness and consistency – of plastic supplied by the sellers, and the sellers' costs of investing in quality. The latter is identified by a policy change which occurred during the sample period. The new regime entitled sellers to a subsidy directly based on the quality of the supplied plastic. Using the estimated primitives of the model, we quantify the efficiency gains from the policy change and evaluate alternative auction designs. The estimates imply that in the benchmark first price auction, the privately provided quality is lower than what is socially optimal. The associated welfare loss is about $5,200$ yen per ton of plastic, or about 5.6% of the average winning bid.

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1 Introduction

Designing market institutions has become increasingly important in practice as evidenced by the recent successes in creating matching markets and designing auctions. Examples range from matching markets for medical residents and school assignment mechanisms for high-school students to auctions for radio spectrum and electricity.[1] While much theoretical and empirical work has been done on mechanism design in static environments, less is understood about the possible consequences of mechanisms when market participants can invest in cost reduction or invest in product quality. These considerations have important policy implications for designing procurement auctions, for example, where there may be social gains from inducing investment by firms. This paper provides empirical evidence on how different mechanisms affect the incentives of agents to invest, and explores the implications for efficient auction design using data from plastic recycling auctions in Japan.

Substantively, the issue of designing efficient mechanisms for plastic recycling is important in its own right. Recycling is considered to be one of the most important ways to deal with the steady increase in the volume of waste and the environmental and health concerns associated with it. Designing mechanisms that make recycling more efficient and economically viable is a common challenge that authorities face in many countries. Our paper provides evidence on how good mechanisms can improve efficiency and increase total welfare.

A common feature of recycling auctions is that the quality of the recyclable material that is supplied and sold often figures importantly in the valuation of the recyclers who buy it. In the case of plastic recycling, for example, the recyclers value the cleanness and the consistency of the supplied plastic as these affect the grade of the recycled resin that they can produce. In Japan, household plastic waste is collected by municipalities, who sell it to recyclers through auctions. Each municipality may invest in the quality of the plastic it supplies by various means. An efficient auction would need to provide the right incentives for the municipalities to invest in quality. This paper examines auction design in such a context.

The incentive issues that arise in auctions when the seller can invest in quality bears close semblance to the problem of the monopolist who sets both prices and quality, studied by Spence (1975). In his paper, Spence finds that the level of quality that is provided by the monopolist is determined by the value that the marginal consumer attaches to quality, whereas the socially

[1] For a survey, see, for example, Milgrom (2004) and Roth (2002)

optimal level of quality is determined by the value attached by the inframarginal consumers. In our auction setting, the socially optimal level of quality is determined by how much value the bidder with the highest valuation attaches to quality.[2] In standard auctions, however, the equilibrium bid of a particular bidder reflects not only the value he attaches to quality, but the value attached by his competitors as well. Hence there is a wedge between the marginal valuation of quality by the bidder with the highest valuation and the seller's marginal revenue from increasing quality. This wedge causes the quality supplied by the seller in standard auctions to be suboptimal.

The recycling auction is well-suited to study the issue of auction design and the incentives to invest, because recyclable plastic is a fairly simple product, where much of the quality differentiation among products can be captured by the cleanness and consistency of plastic, on which data is available. Another important feature of the recycling auctions in Japan is that a policy change took place in the middle of the sample, which was aimed at inducing higher levels of investment in quality from the municipalities. Among other things, the policy change entitled the municipalities to a subsidy if the quality of the supplied plastic exceeded a certain threshold. This policy change plays an important role in identifying the cost function of the municipalities for investing in quality.

Our data consist of a panel of Japanese municipal recycling auctions from 2005 to 2009. We have data on the transaction price, the identity and the characteristics of the winning bidders, and measures of plastic quality supplied by each municipality in each year. Our data come from JCPRA, a not-for-profit auctioneer who handles most of municipal plastic recycling auctions in Japan. In 2009, about $1,000$ municipalities, or close to 60% of all municipalities in Japan, auctioned their plastic through JCPRA, with a total intake of around $604,000$ tons of plastic.

In our analysis, we build a model of plastic recycling auctions and a model of municipality behavior. Our model of the auction is a variant of the first price sealed bid auction with independent asymmetric private values. We recover the distribution of the bids and the values of the bidders as functions of observable auction characteristics, including the quality of the supplied plastic. Our identification and estimation of bid distributions and bidder values follow Guerre, Perrigne and Vuong (2000), and Athey and Haile (2002), although we make parametric assumptions on the bid distributions.

We model the behavior of each municipality as a single agent dynamic programming problem

[2]This is the case if we assume that allocation is efficient, so that the bidder with the highest valuation is also the winner of the auction.

where in each period, it decides how much to invest in quality. The level of investment is determined so that the incremental benefit from investment is equal to the marginal cost. The dynamics in the problem of the municipality arise directly from how the incentive scheme introduced by the policy change is structured: one eligibility criterion for the subsidy requires that the quality of supplied plastic have improved by more than a certain amount compared to the previous year. There is also evidence of important cost linkages across periods which also give rise to dynamics. The primitives of the model, such as the cost function of investment, are estimated using moment conditions based on an intertemporal Euler equation. We exploit the shift in the benefit of investment created by the policy change to identify and estimate the cost function

We find strong evidence that quality is important to the recyclers, and that investing in quality is costly for the municipalities. We also find evidence that in some instances, the incentive scheme introduced by the policy change gives rise to perverse incentives for municipalities to decrease, rather than increase, quality. In our counterfactual experiment, we find that in the benchmark first price auction, the privately provided quality is lower than what is socially optimal. The associated welfare loss is about $5,200$ yen per ton of plastic, or about 5.6% of the average winning bid.

Related Literature This paper is most closely related to the small theoretical literature which studies the relationship between auction design and pre-auction investment, for example Tan (1992), Piccione and Tan (1996), Bag (1997), and Arozamena and Cantillon (2004). This literature analyzes the investment incentives of the bidders under different auction formats and finds that some auction formats induce socially efficient levels of investment while others induce too little.[3] Our paper focuses, instead, on the investment of the seller and finds that auction design has important implications for seller investment as well.

Our paper also contributes to a growing literature on empirical auctions.[4] Our identification and estimation of bid distributions and bidder values draw heavily on the works of Guerre, Perrigne, and Vuong (2000), and Athey and Haile (2002). Our approach to estimating the distribution of the reserve price, which uses variation in the number of bidders and bidder characteristics, is related to results in Athey and Haile (2002), Haile, Hong and Shum (2003), and Guerre Perrigne, and Vuong

[3] For example, in a setup with observable investment and heterogeneous bidders, Aronzamena and Cantillon (2004) finds that second price auctions induce efficient levels of pre-auction investment by bidders while the first price auctions induce too little.

[4] For a recent survey, see for example, Paarsch and Hong (2006), Hendricks and Porter (2007), and Athey and Haile (2008).

(2009).

2 Institutional Details and Data

The Containers and Packaging Recycling Law, which governs much of the way current plastic recycling is done in Japan, was passed in 1995. Among the first in a series of recycling laws passed in the late 1990s and early 2000s,[5] the Law was designed to increase the recycling of container and packaging material, which comprised about 60% of all household waste in terms of volume (or 20% in terms of weight), much of which had been previously treated as waste. In particular, the Law covers the recycling of glass containers, PET bottles, paper containers/packaging, and plastic containers/packaging.

Under the Law, participating municipalities collect and store the four specified types of recyclable materials. Some municipalities are organized into waste management unions which are groups of municipalities that jointly administer household waste management operations. Participation in the recycling of containers and packaging is voluntary: whether to collect containers and packaging as recyclable material is ultimately up to each municipality. In 2009, for example, $1,028$ municipalities, or about 60% of all municipalities, participated in the recycling of plastic containers and packaging. The recyclable materials that are collected by the municipalities are then auctioned by a centralized auctioneer, a not-for-profit entity, which was also created by the Law.

At the time the Law passed, it was projected that the costs of recycling containers and packaging would outweigh the revenues of reselling recycled material. The expectation was that the auction would need to allow for the bids of the recyclers to be negative to have anyone participate in the auctions, and that the municipalities would have to pay the recyclers to have the recyclable material taken away. An important feature of the Containers and Packaging Recycling Law is that it provides full reimbursement of all losses that municipalities incur from the auctions.[6] The cost of paying the recyclers is instead borne by the manufacturers and retailers of containers/packaging (e.g. Coca-cola, Seven Eleven etc.) through a charge based on their proportion of the aggregate quantity of containers/packaging produced or sold in the country.[7] The costs of reimbursing the municipalities

[5]Other related laws include the Home Appliance Recycling Law (1998), the Food Recycling Law (2000), the Construction Waste Recycling Law (2000), and the End-of-Life Vehicle Recycling Law (2002)

[6]The price of some recycleable materials, such as PET bottles, have become positive in recent years. Whenever the price of the auction is positive, the profits accrue to the municipalities.

[7]For example, in 2008, Coca-Cola Japan paid around 556 million yen, or about 6.87 million U.S.D, Seven-Eleven Japan paid around 429 million yen, or about 5.10 million U.S.D.

differ greatly across the type of recyclable material: Plastic containers/packaging auctions make up more than 90% of the total costs, reflecting the fact that the bids for plastic containers/packaging remains well below zero, while the bids for other materials, such as PET bottles, have become positive in recent years. In 2009, for example, the total amount charged to the manufacturers and retailers was around 40.7 billion yen, or 502 million U.S.D., of which 37.5 billion yen, or 463 million U.S.D. was from the costs for plastic containers/packaging auctions.

The bidders in the plastic containers/packaging auctions, which are the auctions that we study in this paper, fall into one of two types, material recyclers and chemical recyclers. Material recyclers are those that transform waste plastic into pellets and fluff which can then be used as inputs to make new plastic. Chemical recyclers are those that decompose waste plastic into various material and gasses that can be used as industrial feedstock. Chemical recyclers can be further divided into four categories, based on the method used for decomposition of plastic: Liquefaction, Coke Oven Chemical Feedstock, Blast Furnace Feed Stock, and Gasification. The distinction between the different types of bidders, especially those between material and chemical recyclers, is important for the auction because qualified material recyclers are given preferential treatment over the chemical recyclers in the auction, as we will discuss more below. The rationale for the preferential treatment of material recyclers is that they are regarded as being more environmentally friendly, directly contributing to the reduction in the use of virgin material.

The recycling technology used to process plastic is quite different for material recycling and chemical recycling, and material recycling is generally considered to be the technology that is more sensitive to the quality of plastic. Low quality plastic with high amounts of impurities is known to translate into low grade plastic pellets and fluff. According to one report, for example, the plastic pellets produced from low quality plastic bales contains, on average, about four times as much chlorine as those produced from high quality plastic bales.[8] The percentage of chlorine and other impurities is a key determinant of prices of plastic pellets and fluff.[9] As for chemical recyclers, quality may matter to them to the extent that low quality plastic bales usually contain high amounts of impurities which damage the pyrolysis furnaces used for chemical decomposition.

[8] See for example, the documents distributed within the working group on recycling methods established under the subcommittee of recycling and waste management within the Ministry of the Environment. http://www.env.go.jp/council/03haiki/y0315-10b.html

[9] See for example, the reference provided during the 15th meeting of the subcommitte on plastic and recycling of the Ministry of Environment. According to the association of material plastic recyclers, it is possible to sell the recycled pellets at a price that exceeds variables costs if, among other things, the chlorine content of the pellets can be reduced to zero. http://www.meti.go.jp/committee/materials2/downloadfiles/g100720c05j.pdf

2.1 The Policy Change

An important policy change occurred in 2006 with the passage of the Amendments to the Containers and Packaging Recycling Law. One of the key features of this new legislation was the introduction of a new payout scheme for municipalities, intended to induce higher levels of effort from the municipalities to improve the quality of supplied material, in particular, the quality of recyclable plastic containers/packaging.[10] It was believed that the municipalities could greatly improve the quality of recyclables at relatively low cost, for example, by monitoring waste drop-off points and through communication with citizens.[11] Before the policy change, the municipalities had no financial incentives to improve the quality of the recyclable plastic they were selling: the winning bids of the plastic auctions were negative, but the municipalities were fully reimbursed for their losses. The new payout scheme, which took effect in 2008, introduced financial incentives to municipalities which were partly based on the measure of plastic quality and partly based on the winning bid.

The first part of the new payment scheme, based on the measure of plastic quality, awards each qualifying municipality a constant amount of money[12] per ton of plastic that is supplied by the municipality. As we will discuss in more detail below, the plastic quality of each municipality is evaluated according to the percent weight of clean plastic that is deemed appropriate for recycling. The municipality is eligible to the payment if the measure of clean plastic either (1) exceeds 95% or (2) exceeds 90% *and* has improved by more than 2% compared to the previous year. Figure 1 illustrates the pairs (q_{t-1}, q_t), the quality measures in year $t-1$ and t, that satisfy the criteria.

The second part of the payment scheme is tied to the winning price. The municipalities are eligible to a fraction (about 40%) of the difference between the winning price and a base price, where the base price is different for each type of recycler. For example, the base price for material recyclers was set at $-94,658$ yen/ton for both 2008 and 2009.[13] If the winning bidder is a material recycler, then the municipality is entitled to a fraction of the difference between the winning bid and $-94,658$ for every ton of plastic that is supplied. If the winning price is below the base price, the municipalities are still compensated in full under the new payment scheme. Finally, a municipality

[10] Similar incentive schemes were introduced by the Amendment for PET bottles, glass bottles, and paper containers/packaging. The combined amount paid to the municipalities in relation to these materials is less than 5% of the total payout, however. Plastic containers/packaging accounts for more than 95% of the total payment.

[11] Another reason why municipalities have a relative cost advantage in cleaning plastic over the recyclers is that cleaning often becomes harder with the passage of time.

[12] $15,560.57$ yen for 2008 and $13,702.02$ yen for 2009.

[13] The base price for liquefaction recyclers was -$84,904$, for coke furnace recyclers, $-62,499$, blast furnace recyclers, $-68,089$, and for gas recyclers, $-65,824$.

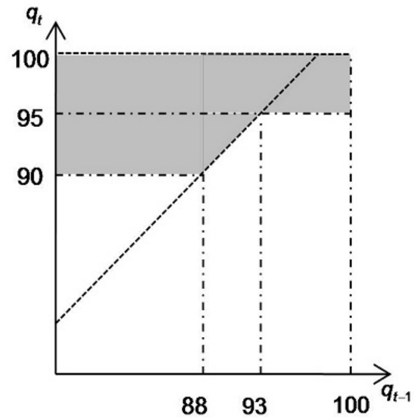

Figure 1: The Shaded Area Corresponds to the pairs (q_{t-1}, q_t) that Satisfy the Criteria to be Eligible for the Subsidy.

can be eligible for either or both of the two parts of the payment scheme. In 2009 for example, about 65% of the municipalities were eligible for the payment from the first part of the payment scheme while almost all of the participating municipalities were eligible to some payout from the second part. Figure 2 illustrates the payout of the municipalities as a function of the winning price. The left panel corresponds to the pre-period and the right panel corresponds to the post-period.

2.2 Auction

The auctions for plastic containers/packaging are held once a year at the beginning of the year, usually in January. The plastic from each municipality is auctioned simultaneously. There is a period of about one month during which potential bidders may submit bids. A bid in the auction is a price per ton of plastic. The winner of the auction is responsible for the intake of plastic that is supplied by the municipality from April of that year to the end of March in the next year and pays the bid times the actual amount of plastic supplied during that period.[14] The bids are submitted electronically, and the submitted bids are not observable to other bidders. Participation in the auction is limited to recyclers who have registered with the auctioneer in advance.

As we mentioned briefly in the previous section, qualified material recyclers are given preferential treatment over the chemical recyclers in the auction.[15] Once the bidding period closes, the bids of

[14] As the winning bid is negative in plastic auctions, the winning bidder actually receives a payment.

[15] The vast majority of material recyclers are given preferential treatment. The number of material recyclers without

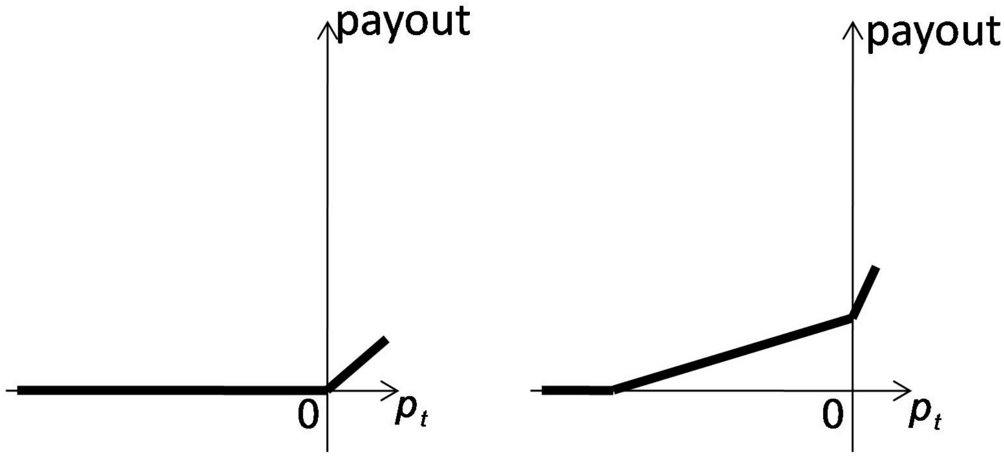

Figure 2: Payout to the Municipality as a Function of the Winning Bid Before the Introduction of the Incentive Scheme and After the Incentive Scheme.

the preferred bidders are opened first. If there is even a single preferred bidder who submits a bid that is higher than the (secret) reserve price, the bidder with the highest bid among the preferred bidders becomes the winner of the auction. When no preferred bidder bids above the reserve price, the bids submitted by the non-preferred bidders are then considered and the winner is determined by the highest bidder among the non-preferred bidders. The non-preferred bidders are also subject to the reserve price, but the reserve price is rarely binding for the non-preferred bidders. For the preferred bidders, the reserve price is often binding. Another important point about the reserve price is that the same reserve price applies to all auctions in a given year.

2.3 Data and Sample Selection

Our data consist of a panel of municipalities and waste management unions that participate in plastic containers/packaging recycling. The auction data is available for five years, from 2005 to 2009 and the measure of plastic quality is available from 2004 to 2009. The auction data consist of the winning bid and the identity of the winner. The losing bids are not observed. Table 1 shows

prefential treatment is about 8 out of a total of 86 on average. Preferential treatment is revoked to material recyclers who fail to meet certain standards required by the auctioneer.

Year	2004	2005	2006	2007	2008	2009
# of Municipalities	490	535	482	491	514	525
# of Unions	110	112	103	108	112	117
Amount (Ton)	446,912	528,528	548,839	581,340	604,486	680,019*

Table 1: Number of Participating Municipalities and Unions. The amount for 2009 is the expected quantity.

the number of participating municipalities and unions from 2004. There are a little more than 500 municipalities and 100 unions participating in plastic recycling each year. The total number of participating municipalities is around $1,000$. Note that there is a drop in the number of participating municipalities and unions from 2005 to 2006. This does not reflect exit, but rather, it is the result of a large wave of municipality mergers that took place around 2005 and reduced the total number of municipalities in Japan from $3,232$ in 2003 to $1,820$ in 2006. We treat a merged municipality as different from any of the merging municipalities except in situations where the merged municipality retains the official municipal code of one of the merging parties. This is the case when the merger is uneven, involving a clear dominant municipality.

In most cases, there is one plastic container/packaging auction for a given municipality per year. In some large municipalities, however, there can be multiple auctions/winners. Large municipalities often have separate auctions for plastic collected from different parts of the municipality. These municipalities are dropped from the sample because it is not possible to link auctions across years for these municipalities.

The data on the quality of supplied plastic is available from 2004. The quality is measured by sampling a bale of compressed plastic, weighing about 60 kilograms. The bale is disassembled and impurities such as dirty plastic and plastic made of unrecyclable resin are sorted and weighed. For the first two years (2004 and 2005) the winning bidder was asked to evaluate the quality of the plastic supplied by the municipalities. While the recyclers were all given the same instructions on how to gauge quality, there was a concern about how closely these instructions were being followed by the recyclers. Staring in 2006, the auctioneer has begun to evaluate the plastic bales directly. In 2006, the auctioneer evaluated about a third (31.65%) of the facilities directly (and the rest were done by the winning bidders). Since 2007, all of the evaluations are conducted by the auctioneer. The inspections are conducted by October and the quality information is released in November or December, before the bidding for the following year takes place. The coverage is not perfect however, and the percentage of municipalities for which the quality measure is available ranges from the low of 90% in 2004 to 99% in 2009.

Lastly, municipalities with very low quality measures and municipalities that do not lie on any of the four main islands of Japan were dropped from the sample. In particular, 6 municipalities whose quality measure fell below 30% and 6 municipalities located in Okinawa and in other remote islands off the four main islands were dropped.[16] This leaves an unbalanced panel of about 400 municipalities and unions per year.

2.4 Sample Statistics

We report the summary statistic of the auctions in Table 2. The average winning bid is around $-83,000$ yen per ton. The winning bid of the qualified material recyclers, who are given preference in the auction as described above, is around $-92,000$ yen, about $10,000$ yen lower than the mean. For non-preferred recyclers, the average is about $-67,000$ yen. It may seem like the average winning bid of the non-preferred material bidders is substantially higher than the average winning bid of other non-preferred bidders. This reflects the fact that non-preferred material recyclers are concentrated in the last few years of the panel when the winning bid was generally higher. When we look within a year, the price difference between the non-preferred material recyclers and other non-preferred recyclers vanishes.

The distance between the municipality and the location of potential bidders is an important factor in the auction. On average, the distance between the municipality and the closest material recycler is about 40 kilometers ($\approx$25 miles) and 95 kilometers ($\approx$60 miles) for the nearest chemical recycler. In terms of the distance between the municipality and the winning bidder, it is about 100 kilometers when the winner of the auction is a material recycler and 200 kilometers when the winner is a chemical recycler. The average quantity of plastic supplied by a municipality in a given year is a little more than 500 tons. The mean payment from the municipality to the winning bidder is about 42 million yen (520 thousand U.S.D). Table 3 shows the number of registered recyclers by type.

Table 4 presents the average quality of the plastic bales, as measured by the percent weight of

[16] The six municipalities that were dropped are Ishikari-shi, Kashihara-shi, Kokubunji-shi, Maebashi-shi, Matsudo-shi, Shimizu-cho. The 6 cases in which the quality fell below 30% are outliers: These counts are more than 10% lower than the next worst municipality. The decision to drop these cases is motivated by the fact that the quality measure at such low levels is very noisy, affected to a large extent by the choice of the bale that is sampled. The municipalities outside of the main islands were dropped because their prices are very low compared to others and the bids are not subject to the reserve price.

		N
Price (yen)	−82834.03 (20805.38)	2502
Price of Qualified Material Recyclers (Preferred)	−93288.35 (16854.12)	1495
Avg. Price of Non-Preferred	−67313.47 (15834.59)	1007
Liquefaction Recyclers	−89410.28 (13731.06)	108
Gas Recyclers	−65482.44 (12653.99)	89
Coke Furnace Recyclers	−65910.46 (12134.45)	515
Blast Furnace Recyclers	−75821.72 (19262.13)	109
Unqualified Material Recyclers	−54257.87 (6809.96)	186
Distance from Winning Bidder (km)	131.97 (152.10)	2502
Winning Bidder is Material	97.81 (84.85)	1681
Winning Bidder is Chemical	201.91 (220.28)	821
Distance from Nearest Material Recycler (km)	42.88 (52.07)	2502
Distance from 2nd Nearest Material Recycler (km)	64.10 (58.85)	2502
Distance from Nearest Chemical Recycler (km)	96.51 (71.12)	2502
Distance from 2nd Nearest Chemical Recycler (km)	154.03 (88.75)	2502
Quantity (ton)	501.44 (974.97)	2502

Table 2: Descriptive Statistics of Auctions. Standard errors are in parenthesis.

	Total	Preferred	Not-Preferred
# of Material Recyclers	86.2	77.8	8.4
# of Chemical Recyclers	16.2	0	16.2
# of Liquefaction	1.8	0	1.8
# of Blast Furnace	3.0	0	3.0
# of Coke Furnace	6.6	0	6.6
# of Gassification	4.8	0	4.8

Table 3: Number of Registered Recyclers by Year and Type of Recycler

Year	2004	2005	2006	2007	2008	2009
plastic content (measured by recycler)	94.98 (5.64)	95.47 (5.06)	93.27 (7.18)	–	–	–
plastic content (measured by auctioneer)	–	–	83.88 (12.25)	91.52 (9.48)	92.49 (8.24)	93.61 (7.19)

Table 4: Average Plastic Content by Year. Standard errors in parenthesis.

plastic judged to be recyclable, for each year since 2004. Recall that for the first two years of the sample (2004 and 2005), the measurement of quality was done by the winning bidder. In 2006, the auctioneer carried out the measurement for about a third of the municipalities directly, while the rest were measured by the winning bidder as before. Since 2007, all of the facilities are evaluated by the auctioneer. The two rows in Table 4 correspond to the average plastic quality of municipalities inspected by the recyclers (top row) and by the auctioneer (bottom row). Note that in 2006, the average plastic quality of the municipalities that were inspected by the recyclers is very low: This partly reflects selection, as municipalities that were inspected directly were not chosen randomly, and partly reflects the difference in how strictly the recyclers and the auctioneer apply the criteria used to assess plastic quality.

Note that quality also drops between 2005 and 2006 for municipalities whose quality was measured by the recycler. This is likely due to the fact that the auctioneer specifically requested a more stringent application of the criteria in assessing plastic bales to recyclers that year. In the following analysis, we treat the quality measurements conducted by the auctioneer in 2006, 2007, 2008 and 2009 as comparable across the years. We will also treat the measurements from the first two years as equivalent. Regarding the measurements conducted by the recyclers in 2006, we allow for the possibility that they are different from the measurements in other years.

2.5 Preliminary Analysis

In this section, we present results from regressions which motivate and help structure the analysis below. The first set of results, reported in Table 5, are estimates obtained from regressing the winning bid on quality and other observable characteristics of the auction. The regression that we ran is

$$p_{mt} = \alpha_m + \beta_1 \cdot q_{mt-1} + \beta_2 \cdot X_{mt} + YEAR + \varepsilon_{mt}$$

where p_{mt} is the price of the winning bid for municipality m in year t, α_m is the municipality effect (FE/RE), q_{mt-1} is the quality of plastic in the previous year, X_{mt} is a vector of auction characteristics such as the distance between the municipality and the closest material recycler, and finally $YEAR$ are year dummies. The results of Table 5 were obtained by running the regression only on the subset of the sample where q_{mt-1} is measured by the auctioneer. This subset basically consists of a three year panel (t = 2007, 2008, 2009) of municipalities that were inspected by the auctioneer in 2006-2008 and a two year panel of municipalities that were inspected by the auctioneer only in 2007 and 2008. The first two columns report results obtained with municipality fixed effects and the last two columns present results with random effects. First, note that the coefficient on Quality is *negative* in all four specifications and is statistically significant in the last two columns. That is, there is a negative relationship between quality and the winning bid. Note also that the coefficient on the Distance to Closest Material Recycler appears *positive* and significant in specifications (2) and (4), implying that on average, the winning bid is higher the further away the nearest material recycler is.[17]

In order to understand the reason for these counterintuitive results, consider the results reported in Table 6 which correspond to the following logistic regression,

$$Preferred_{mt} = 1\{\alpha_m + \beta_1 \cdot q_{mt-1} + \beta_2 \cdot X_{mt} + YEAR + \varepsilon_{mt} \geq 0\}.$$

The dependent variable, $Preferred_{mt}$, is a dummy variable which is equal to 1 if the winner is a preferred recycler, and 0 otherwise. Note that in all specifications, the coefficient on Quality is positive: higher plastic quality is associated with higher probability of a preferred recycler winning

[17] When we run the same regression on a two year (t = 2005, 2006) panel, the results are not as strong. However, the coefficient on Quality is not positive and statistically significant in any of the specifications. Moreover, the coefficient on Quality is negative when we control for distance and include fixed effects [specification (2)]. The coefficient on Distance to the Nearest Material Recycler is also positive, while not statistically significant.

Dep. Var: Winning Bid	(1)	(2)	(3)	(4)
Quality	-86.50	-100.04	-181.01^{***}	-179.82^{**}
	(107.46)	(106.91)	(70.63)	(73.94)
Distance to Closest Material Recycler	–	128.04^{***}		49.59^{**}
		(37.63)		(25.42)
Distance to 2nd Closest Material Recycler	–	-13.26		-60.64^{***}
		(46.25)		(24.44)
Distance to Closest Chemical Recycler	–	17.02		-10.50
		(13.29)		(12.28)
Distance to 2nd Closest Chemical Recycler	–	-48.92		17.32
		(38.63)		(11.31)
FE	Yes	Yes	No	No
Time Dummy	Yes	Yes	Yes	Yes
N	528	528	528	528

Table 5: Regression of the Winning Bid on Quality, Distance from Recyclers and Time Dummies. The results of the first two columns are with Municipality F.E. and the last two columns are with R.E. The winning bid is Yen/Ton of plastic. Standard errors in parenthesis.

the auction. Note also that the coefficient on the Distance to Closest Material Recycler is negative and statistically significant, as we would expect. The results we obtain are qualitatively similar if we instead use the first two years of the panel (t = 2004, 2005) to run this regression[18] or if we change the specification to Probit.

Recall that the average winning bid of the preferred recyclers is about $-92,000$ yen, while the average winning bid of the non-preferred recycler is about $-67,000$. Figure 3 shows the histogram of the winning bids of the preferred bidders in the top panel and the non-preferred bidders in the bottom panel, for 2009. Note that the distribution of bids of the material recyclers are truncated at $-93,000$, which was the reserve price for 2009. The previous logit regression results suggest that lower quality or longer distance to the closest material recycler make it more likely that no preferred bidder bids above the reserve price. This in turn, increases the probability that the winner of the auction is a non-preferred bidder, who submits higher bids than the preferred bidders on average. Another way to put it is that higher quality and shorter distance induce changes in the type of winner and this effect may dominate the direct effect on prices.

In order to substantiate this reasoning, we ran the following regression using Maximum Likeli-

[18]We can only run the RE specification because the panel length is 2.

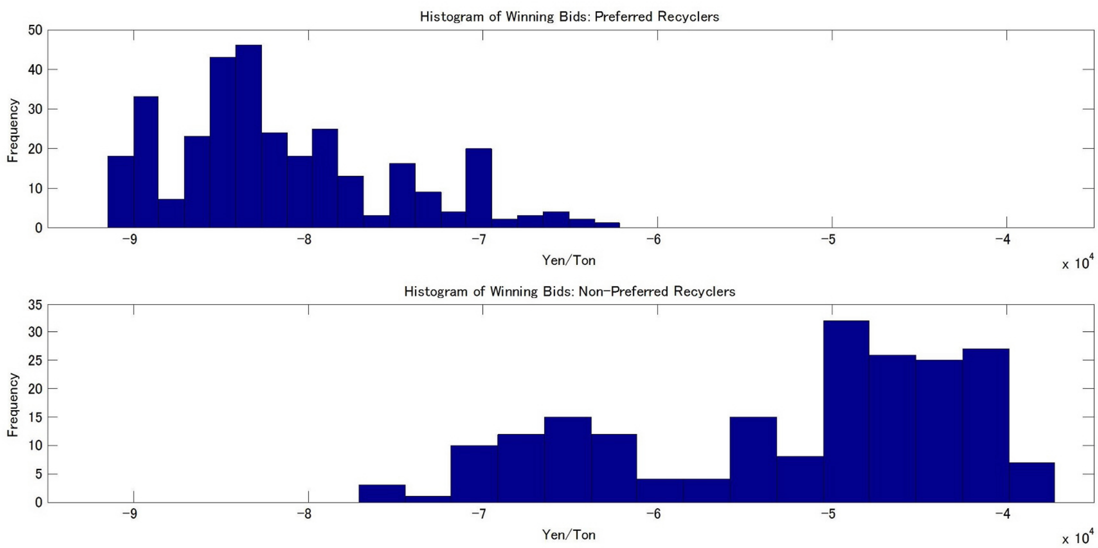

Figure 3: Histogram of The Winning Bids for 2009. The top panel corresponds to the preferred recyclers and the bottom panel corresponds to the non-preferred recyclers. The reservation price for 2009 was $-93,000$.

Dep. Var: Preferred Bidder Dummy	(1)	(2)	(3)	(4)
Quality	0.0534^{**}	0.0507^{*}	0.0541^{***}	0.0564^{***}
	(0.0274)	(0.0294)	(0.0163)	(0.0160)
Distance to Closest Material Recycler	–	-0.0400^{**}		-0.0284^{***}
		(0.0171)		(0.0060)
Distance to 2nd Closest Material Recycler	–	0.0068		0.0071
		(0.0089)		(0.0047)
FE	Yes	Yes	No	No
Time Dummy	Yes	Yes	Yes	Yes
N	138	138	528	528

Table 6: Logistic Regression of the Type of the Winning Bider on Quality and Distance from the Two Closest Material Recyclers with Municipality F.E./R.E. and Time Dummies. Standard errors in parenthesis.

hood:

$$
\begin{aligned}
p_{mt} &= p^P_{mt} \cdot 1\{p^P_{mt} \geq R_t\} + p^{NP}_{mt} \cdot 1\{p^P_{mt} < R_t\} \\
p^P_{mt} &= \beta^P_0 + \beta^P_1 q_{mt-1} + \beta^P_2 X^P_t + YEAR + \varepsilon^P_{mt}, \;\; \varepsilon^P_{mt} \sim N(0, \sigma^P) \\
p^{NP}_{mt} &= \beta^{NP}_0 + \beta^{NP}_1 q_{mt-1} + \beta^{NP}_2 X^{NP}_t + YEAR + \varepsilon^{NP}_{mt}, \;\; \varepsilon^{NP}_{mt} \sim N(0, \sigma^{NP}),
\end{aligned}
$$

where p_{mt} is the winning bid, p^P_{mt} and p^{NP}_{mt} are the highest bids among the preferred recyclers and the non-preferred recyclers, respectively. The first equation captures the fact that the bid that we observe, p_{mt}, is equal to p^P_{mt} if p^P_{mt} is higher than the reserve price, R_t, and that p_{mt} is equal to p^{NP}_{mt}, otherwise. We report the baseline results without any controls in the first column of Table 7 and the results with distance as control variables in the second column. The results seem to largely bear out our earlier reasoning. Notice that the coefficients on Quality is positive and significant for the material recyclers in both columns 1 and 2. The coefficient on Quality is also positive for the chemical recyclers and becomes significant in our second specification. Note also that the coefficients on Distance to the Closest Material Recycler and Distance to the Closest Chemical Recycler are both negative and statistically significant as expected. This is in stark contrast to the results from the first set of regressions reported in Table 5. In those set of regressions, the direct effect of quality and distance on the winning bid is confounded with the indirect effect which arises through the change in the type of the winning bidder. The results in Table 5 suggest that the direct effect is dominated by the negative indirect effect, but the results in Table 7 suggest that direct effect is positive and

Dep. Var: Winning Bid	(1)	(2)	(3)	(4)
Quality for Preferred Recycler (β_1^P)	147.31***	145.61***	147.46***	146.22***
	(45.07)	(38.05)	(41.20)	(40.97)
Quality for Non-Preferred Recycler (β_1^P)	46.47	64.42**	40.86	62.94**
	(29.58)	(28.23)	(29.85)	(28.54)
Quality for Preferred Recycler (Contemporary)	–	–	24.97	20.24
			(45.37)	(45.23)
Quality for Non-Preferred Recycler (Contemporary)	–	–	18.92	2.12
			(39.25)	(37.41)
Distance to Closest Material Recycler	–	−35.09**	–	−35.26**
		(14.11)		(14.30)
Distance to 2nd Closest Material Recycler	–	14.77	–	15.80
		(12.47)		(12.61)
Distance to Closest Chemical Recycler	–	−35.29***	–	−39.03***
		(9.38)		(9.42)
Distance to 2nd Closest Chemical Recycler	–	14.96	–	19.26**
		(9.20)		(9.24)
Prefecture Dummy	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes
N	1027	1027	1016	1016

Table 7: Regressions of the Winning Bid on Quality, Current Year Quality and Other Auction and Bidder Characteristics. The regressions all include prefecture dummies and year dummies. The winning bid is Yen/Ton. Estimated by Maximum Likelihood. Standard errors are in parenthesis.

significant. Again, we obtain similar results when we use the first two years of the sample ($t = 2004$, $t = 2005$).

The last two columns of Table 7 show the results from the maximum likelihood regression with the addition of year t quality, q_t as a control variable. The measurements of plastic quality for a year t is taken in the spring or in the summer and the information becomes public around November or December of that year. From the perspective of the bidders, what is important is current-year quality, q_t, and not q_{t-1}, but the information that is available at the time of bidding is q_{t-1}. The results in the last two columns of Table 7 is consistent with this view. While the coefficient on Quality remains positive and statistically significant, the coefficient on current-year quality is not statistically significant.

The next set of results are related to the effect of the payment scheme on the behavior of municipalities. Starting in 2008, the municipalities are eligible to receive a fraction of the difference between the winning price and the base price as well as a payout based on whether the quality exceeds a certain threshold. Table 8 reports the fraction of municipalities that exceeded the threshold for

2007, 2008 and 2009. The fraction is computed using the full sample for 2008 and 2009, while for 2007, it was computed only for those municipalities whose quality was measured by the auctioneer. 2007 is the pre-period year and 2008 and 2009 are the post-period years. While the improvement in the mean quality was not much more than 2% from 2007 to 2009 as we saw in Table 4, the fraction of municipalities that satisfy the quality threshold increased by more than 10%.

In order to further assess the effect of the payment scheme on quality, we report the results of the following regressions designed to capture the differential effect of the payment scheme for municipalities and waste management unions:

$$\begin{aligned} q_{mt} &= \alpha_m + \beta_1 q_{mt-1} + \beta_2 \cdot Incentives_{mt} + \varepsilon_{mt} \\ q_{mt} &= \alpha_m + \beta_1 q_{mt-1} + \beta_2 \cdot Incentives_{mt} + \beta_3 \cdot Incentives_{mt} \times Union + \beta_3 \cdot Union + \varepsilon_{mt}, \end{aligned}$$

where q_{mt} and q_{mt-1} denote the current-period quality and previous-year quality, α_m is the municipality fixed effect, $Incentives_{mt}$ is a dummy variable which takes 1 when $t = 2008$ or $t = 2009$, and $Union$ is an indicator variable for waste management unions. The results are obtained by running fixed effects regressions using the full set of municipalities for 2008, 2009 and the subset of municipalities for 2007 whose quality was measured by the auctioneer in 2006. Table 9 reports the results. The first column of Table 9 presents the results of the first regression when we restrict the sample to municipalities that do not belong to a union. The second column shows the results for the same regression, but when the sample is taken to be just the set of waste management unions. Note that the coefficient on $Incentives_{mt}$ is positive and statistically significant in the first column, while it is smaller and not significant for unions. The third column reports the same regression with the interaction term, $Incentives_{mt} \times Union$. Allthough the coefficient on the interaction term is not statistically significant, it is negative, suggesting that the effect of incentives was smaller on unions than on municipalities. This is consistent with the notion that when compensation is based on the output of a team rather than the individual, there is a free-riding problem. Some of the steps that are needed to improve quality occurs at the level of municipalities, such as sending municipality employees to monitor waste drop-off points or communicating with citizens about what and what not to recycle. The results are largely consistent with the prediction that the effect of introducing the incentive scheme would be larger for municipalities and smaller for unions.

These results seem to suggest that the incentive scheme put in place in 2008 induced munici-

Year	2007	2008	2009
% of Municipalities exceeding 95% or exceeding 90% and improving by more than 2%	54.54%	57.25%	65.26%

Table 8: The Fraction of Municipalities that Exceeded the Quality Threshold.

Dep. Var: Quality	(1)	(2)	(3)
Lagged Quality	-0.0293	0.0131	-0.0215
	(0.0399)	(0.0782)	(0.0361)
Incentives	2.1688^{***}	0.9835	2.1433^{***}
	(0.3592)	(0.7567)	(0.3726)
Incentives×Union			-0.9174
			(0.9904)
Sample	Muni	Union	All
FE	Yes	Yes	Yes
N	426	92	518

Table 9: Fixed Effects (Arrelano-Bond) Regression of Current Year Quality on Previous Year Quality, Incentives Dummy, Union Dummy, and Incentives Dummy Interacted with Union Dummy. Standard errors in parenthesis.

palities to improve the quality of plastic. However, the interpretation of these results is somewhat difficult as not all of the municipalities had incentives to raise quality in 2008 and 2009. Recall that the incentive scheme has two components, a lump sum payout based on the quality, and a payout which is proportional to the difference between the winning bid and the base price. The second component can actually create negative incentives for quality enhancement for some municipalities. The reason for this is that increasing quality can make the winning bid lower, as we saw in Table 5. Now, it is true that the base price is adjusted for each type of winner to counteract the perverse incentives to decrease quality. For example, the base price is $-94,658$ yen for material recyclers, while it is $-65,824$ yen for gasification recyclers.[19] But the differences in the base price may be inadequate. For example, the average winning price for the material recyclers in 2009 is around $-79,000$, (which is about $15,000$ yen higher than the base price) and the mean winning price for gasification recyclers is about $-40,000$ (which is about $25,000$ yen higher than the corresponding base price). This is despite the fact that the average quality of plastic that material recyclers won was more than 5% higher than those of gasification recyclers.

To more precisely quantify the effect of the payout scheme and recover primitives such as valu-

[19] The base prices for other recyclers are $-84,904$ yen (liquefaction), $-68,089$ yen (blast furnace), and $-62,499$ yen (coke furnace).

ations of bidders and the cost of investing in quality for the municipalities, we build a model and structurally estimate it in the next two sections. In the structural estimation, we use the auction data of both municipalities and unions, but for the estimation of the cost function, we use only the data from the municipalities. As regards the change in the measurement of quality, we allow for the possibility that the quality measures may not be comparable across years. We only treat the quality measurements conducted by the auctioneer from 2006 through 2009 as equivalent and the measurements from the first two years as equivalent. In particular, we do not assume that the measurements taken in 2006 by the winning bidder are comparable to the measures of any other year. In practice, we estimate coefficients on quality in the bid distribution and in the cost function of the municipalities that differ depending on the year.

3 Model

In this section, we lay out the model used to structure the empirical analysis. We will describe the auction model first and then present the model of municipality behavior.

3.1 Auction

Our model of the auction is a variant of the first price sealed-bid auction, consisting of two stages with preferred bidders and non-preferred bidders. In the first stage, only the bids of the preferred bidders are considered. If there is even a single preferred bidder who submits a bid that is higher than the secret reserve price R_t, the auction ends in the first stage and the preferred bidder who submits the highest bid wins the auction. Only when no preferred bidders bid above R_t, are the bids of the non-preferred bidders considered. In the second stage, just as in the first, the non-preferred bidder who submits the highest bid wins the auction, subject to the reserve price. The bidding takes place simultaneously for both the preferred and the non-preferred bidders.

Let N_P and N_{NP} be the number of preferred and non-preferred bidders respectively. Let U_{ij} be the per-unit value of plastic to bidder i in auction j, drawn from a CDF, F_{ij}, with continuous density f_{ij}. U_{ij} is the private value to the firm which may reflect business opportunities or operating costs of bidder i. F_{ij} may depend on the type of recycler (e.g. Material, Gas, etc.), the expected quality of the plastic waste being sold in the auction, $q^e_j = E[q_j]$, the distance between the municipality and the recycler, d_{ij}, as well as other observable bidder characteristics. Conditional on these auction and bidder characteristics, we assume that U_{ij} is i.i.d. across i (but not necessarily across j). Our model of the auction is thus an asymmetric independent private values model.[20] We can write the problem of the preferred bidder as follows,

$$\max_{b_{ij}} \Pr(b_{ij} \geq R_t)(U_{ij} - b_{ij})G_{ij}(b_{ij})$$

where b_{ij} denotes bidder i's bid and G_{ij}, denotes the cumulative distribution function of the highest bid among $N_P - 1$ preferred rivals of bidder i. The first-order condition is given by

$$U_{ij} = b_{ij} + \frac{1}{\frac{\frac{\partial}{\partial b}\Pr(b \geq R_t)}{\Pr(b \geq R_t)} + \frac{g_{ij}(b_{ij})}{G_{ij}(b_{ij})}},$$

where g_{ij} is the density of G_{ij}. Note that this expression reduces to the familiar formula, $U_{ij} = b_{ij} + \frac{G_{ij}(b_{ij})}{g_{ij}(b_{ij})}$ if we set $\Pr(b \geq R_t) = 1$ and $\frac{\partial}{\partial b}\Pr(b \geq R_t) = 0$. Next consider the problem of the non-preferred bidders. If we let P_{NP} be the probability that no preferred bidder wins the auction, the problem of the non-preferred bidders is

$$\max_{b_{ij}} \Pr(b_{ij} \geq R_t) \cdot P_{NP} \cdot G_{ij}(b_{ij})$$

where G_{ij} is now the C.D.F. of the highest bid among $N_{NP} - 1$ non-preferred bidders. The first-order condition for the non-preferred bidders are the same as for the preferred bidders.

3.2 Municipalities

The model of the municipalities is a single-agent dynamic programming problem, where at each period t, the municipality chooses the level of effort e_t to maximize utility. We let the evolution of quality q_t follow the process,

$$q_t = H(\alpha q_{t-1} + e_t + \varepsilon_t).$$

where α is a constant, and ε_t is a i.i.d random shock, and H is a strictly increasing function with $\lim_{t \to -\infty} H(t) = 0$ and $\lim_{t \to +\infty} H(t) = 1$. Let $R_t(e_t, q_{t-1})$ denote the return function, that is, the benefit to the municipality of exerting effort (investment) e_t given q_{t-1}. For 2005, 2006 and 2007,

[20] There exists a pure strategy equlibrium in monotone strategies. See Reny and Zamir (2003).

$R_t(\cdot,\cdot)$ is simply equal to the non-pecuniary utility from providing quality q_t:

$$R_t(e_t, q_{t-1}) = E[U(q_t)] = E_{\varepsilon_t}[U(H(\alpha q_{t-1} + e_t + \varepsilon_t))],$$

where $U(\cdot)$ can be interpreted as a warm glow payoff. Recall that the winning bids are negative and that municipalities are compensated for any losses. For years 2008 and 2009, the municipalities are entitled to a monetary payout depending on the values of (q_t, q_{t-1}):

$$R_t(e_t, q_{t-1}) = E[B_t \cdot 1\left(\{q_t \geq 95\} \cup (\{q_t \geq 90\} \cap \{q_t - q_{t-1} \geq 2\})\right)] + r_t(E[q_t]) + E[U(q_t)]$$

where the first term of the right hand side of the above expression captures the payout from satisfying the quality threshold, and the second term, $r_t(E[q_t])$, captures the payout from the auction that is proportional to the difference between the winning bid and the base price. Finally, B_t is the fixed amount per ton that is paid to eligible municipalities. Now, if we let $C(e_t)$ denote the cost of exerting effort, the problem of the municipality is

$$\begin{aligned} V_t(q_{t-1}) &= \max_{e_t} R_t(e_t, q_{t-1}) - C(e_t) + \beta E[V_{t+1}(q_t)] \\ s.t.\ q_t &= H(\alpha q_{t-1} + e_t + \varepsilon_t). \end{aligned}$$

The first-order condition associated with this problem is

$$\frac{\partial}{\partial e_t} R_t(e_t, q_{t-1}) - \frac{\partial}{\partial e_t} C(e_t) + \beta \frac{\partial}{\partial e_t} E[V_t(H(\alpha q_{t-1} + e_t + \varepsilon_t))] = 0.$$

The above expression can be rewritten using the Euler equation as follows[21]:

[21] Consider the following variational argument. Suppose we increase e_t by de_t, and for each realization of q_t, we decrease e_{t+1} by $-\alpha H'(H^{-1}(q_t)) \cdot de_t$. This keeps the distribution of the winning bids in years $\tau \geq t+1$ unchanged. The year t change in the utility is $\frac{\partial}{\partial e_t} R_t(e_t, q_{t-1}) - \frac{\partial}{\partial e_t} C(e_t)$, while the year $t+1$ change in the utility is $\beta E_t \left[\alpha H'(H^{-1}(q_t)) \left\{ \frac{\partial}{\partial e_{t+1}} R_{t+1}(e_{t+1}, q_t) - \frac{\partial}{\partial e_{t+1}} C(e_{t+1}) \right\}\right]$. $\frac{\partial}{\partial e_{t+1}} R_{t+1}(e_{t+1}, q_t)$ is $E[U'(q_{t+1}) H'(H^{-1}(q_{t+1}))]$ for $t \leq 2006$, and $\frac{\partial}{\partial e_{t+1}} R_t(e_{t+1}, q_t)$ is $B_{t+1} 1_{\{q_t \in [88,93]\}} f_{q_t}(q_t + 2) + E[U'(q_{t+1}) H'(H^{-1}(q_{t+1}))]$ for $t \geq 2007$.

$$
\begin{aligned}
&\frac{\partial}{\partial e_t}R_t(e_t, q_{t-1}) - \frac{\partial}{\partial e_t}C(e_t) + \\
&\beta E\left[\alpha H'(H^{-1}(q_t))\left\{\frac{\partial}{\partial e_{t+1}}C(e_{t+1}) - U'(q_{t+1})H'(H^{-1}(q_{t+1}))\right\}\right] = 0 \qquad t \leq 2006 \\
&\frac{\partial}{\partial e_t}R_t(e_t, q_{t-1}) - \frac{\partial}{\partial e_t}C(e_t) + \\
&\beta E\left[\alpha H'(H^{-1}(q_t))\left\{\begin{array}{c} \frac{\partial}{\partial e_{t+1}}C(e_{t+1}) - U'(q_{t+1})H'(H^{-1}(q_{t+1})) \\ -B_{t+1}1_{\{q_t\in[88,93]\}}f_{q_{t+1}}(q_t+2)H'(H^{-1}(q_t+2)) \end{array}\right\}\right] = 0 \quad t \geq 2007,
\end{aligned}
$$

where f_{q_t} denotes the density function of q_t given q_{t-1} and e_t. Note that $R_t(e_t, q_{t-1})$ is differentiable, with $\frac{\partial}{\partial e_t}R_t(e_t, q_{t-1}) = E[U'(q_t)H'(H^{-1}(q_t))]$ and $\frac{\partial}{\partial q_{t-1}}R_t(e_t, q_{t-1}) = \alpha E[U'(q_t)H'(H^{-1}(q_t))]$, for t = 2005, 2006, and 2007. For t = 2008 and 2009, $\frac{\partial}{\partial e_t}R_t(e_t, q_{t-1})$ and $\frac{\partial}{\partial q_{t-1}}R_t(e_t, q_{t-1})$ can be expressed as follows[22],

$$
\begin{aligned}
&\frac{\partial}{\partial e_t}R_t(e_t, q_{t-1}) \\
= &\begin{cases}
B_t f_{q_t}(95)\cdot H'(H^{-1}(95)) + E[U'(q_t)H'(H^{-1}(q_t))] + r_t'(E[q_t])E[H'(H^{-1}(q_t))] & \text{if } q_{t-1} \geq 93 \\
B_t f_{q_t}(q_{t-1}+2)\cdot H'(H^{-1}(q_{t-1}+2)) + E[U'(q_t)H'(H^{-1}(q_t))] + r_t'(E[q_t])E[H'(H^{-1}(q_t))] & \text{if } 88 \leq q_{t-1} \leq 93 \\
B_t f_{q_t}(90)\cdot H'(H^{-1}(90)) + E[U'(q_t)H'(H^{-1}(q_t))] + r_t'(E[q_t])E[H'(H^{-1}(q_t))] & \text{if } q_{t-1} \leq 88
\end{cases}
\end{aligned}
$$

[22] Consider the case when t = 2008 or 2009 and that $q_{t-1} \geq 93$. Then, $\frac{\partial}{\partial e_t}R_t(e_t, q_{t-1}) = \frac{\partial}{\partial e_t}E[B_t\cdot 1\{\alpha q_{t-1}+e_t+\varepsilon_t \geq H^{-1}(95)\}] + \frac{\partial}{\partial e_t}r_t(E[H(\alpha q_{t-1}+e_t+\varepsilon_t)]) + \frac{\partial}{\partial e_t}E[U(H(\alpha q_{t-1}+e_t+\varepsilon_t))]$. Consider each term in the expression in turn. If we denote the distribution of ε as F_ε, $E[B_t\cdot 1\{\alpha q_{t-1}+e_t+\varepsilon_t \geq H^{-1}(95)\}] = B_t\cdot \Pr(\varepsilon_t \geq H^{-1}(95)-\alpha q_{t-1}-e_t) = B_t\cdot(1-F_\varepsilon(H^{-1}(95)-\alpha q_{t-1}-e_t))$. Hence, $\frac{\partial}{\partial e_t}E[B_t\cdot 1\{\alpha q_{t-1}+e_t+\varepsilon_t \geq H^{-1}(95)\}] = B_t\cdot f_\varepsilon(H^{-1}(95)-\alpha q_{t-1}-e_t)$. Note that $F_{\dot{q}_t}(s) \equiv \Pr(q_t \leq s) = \Pr(\alpha q_{t-1}+e_t+\varepsilon_t \leq H^{-1}(s)) = \Pr(\varepsilon_t \leq H^{-1}(s)-\alpha q_{t-1}-e_t) = F_\varepsilon(H^{-1}(s)-\alpha q_{t-1}-e_t)$.
By taking derivatives of the above expression with respect to s, we obtain $f_{q_t}(s) = f_\varepsilon(H^{-1}(s) - \alpha q_{t-1} - e_t)\cdot\left(H^{-1}\right)'(s)$. Hence, $\frac{\partial}{\partial e_t}E[B_t\cdot 1\{\alpha q_{t-1} + e_t + \varepsilon_t \geq H^{-1}(95)\}] = B_t\cdot f_{q_t}(H^{-1}(95)\cdot H'(H^{-1}(95))$. As for $\frac{\partial}{\partial e_t}r_t(E[H(\alpha q_{t-1}+e_t+\varepsilon_t)])$, $\frac{\partial}{\partial e_t}r_t(E[H(\alpha q_{t-1}+e_t+\varepsilon_t)]) = r_t'(E[H(\alpha q_{t-1}+e_t+\varepsilon_t)])E[H'(\alpha q_{t-1}+e_t+\varepsilon_t)] = r_t'(E[q_t])E[H'(H^{-1}(q_t))]$ and similarly, we obtain that $\frac{\partial}{\partial e_t}E[U(H(\alpha q_{t-1}+e_t+\varepsilon_t))] = E[U'(q_t)H'(H^{-1}(q_t)]$.

and

$$
\frac{\partial}{\partial q_{t-1}} R_t(e_t, q_{t-1})
$$

$$
= \begin{cases} B_t \alpha f_{q_t}(H^{-1}(95)) \cdot H'(H^{-1}(95)) + \alpha E[U'(q_t) H'(H^{-1}(q_t))] + \alpha r_t'(E[q_t]) E[H'(H^{-1}(q_t))] \\ \hfill \text{if } q_t \geq 93 \\ -B_t(1-\alpha) f_{q_t}(q_{t-1}+2) \cdot H'(H^{-1}(q_{t-1}+2)) + \alpha E[U'(q_t) H'(H^{-1}(q_t))] + \alpha r_t'(E[q_t]) E[H'(H^{-1}(q_t))] \\ \hfill \text{if } 88 \leq q_t \leq 93 \\ B_t \alpha f_{q_t}(H^{-1}(90)) \cdot H'(H^{-1}(90)) + \alpha E[U'(q_t) H'(H^{-1}(q_t))] + \alpha r_t'(E[q_t]) E[H'(H^{-1}(q_t))] \\ \hfill \text{if } q_t \leq 88 \end{cases} .
$$

Finally, the Euler equation implies that

$$
E_{q_t}\left[\begin{array}{c} \frac{\partial}{\partial e_t} R_t(e_t, q_{t-1}) - \frac{\partial}{\partial e_t} C(e_t) \\ +\beta \alpha H'(H^{-1}(q_{t+1})) \left\{ \frac{\partial}{\partial e_{t+1}} C(e_{t+1}) - U'(q_{t+1}) H'(H^{-1}(q_{t+1})) \right\} \end{array} \middle| \Omega_t \right] = 0 \qquad t \leq 2006
$$

$$
E_{q_t}\left[\begin{array}{c} \frac{\partial}{\partial e_t}(e_t, q_{t-1}) - \frac{\partial}{\partial e_t} C(e_t) + \beta \alpha H'(H^{-1}(q_t)) \Big(\frac{\partial}{\partial e_{t+1}} C(e_{t+1}) \\ -U'(q_{t+1}) H'(H^{-1}(q_{t+1})) - B_{t+1} 1_{\{q_t \in [88,93]\}} f_{q_{t+1}}(q_t+2) H'(H^{-1}(q_t+2)) \Big) \end{array} \middle| \Omega_t \right] = 0 \qquad t \geq 2007,
$$

where Ω_t is the information set of the municipality at time t when it chooses its level of effort, e_t. Note that Ω_t obviously includes q_{t-1}, but is also includes variables such as the number of potential bidders and their characteristics. Because the number of potential bidders and the characteristics of the bidders affect $r_t(\cdot)$, they also affect the municipality's choice of e_t.

3.3 Discussion of the Modelling Assumptions

We discuss some of our modelling choices in this section. Recall that in our model of the auction, the bidders' valuations are taken to be independent and private (IPV). First, note that the independent values assumption does not rule out unconditional dependence of the bidders' values. Indeed, the bidders' values are modeled as functions of bidder characteristics and auction characteristics, and there will be correlation among the values, unconditionally. The independent values assumption only rules out conditional dependence of the bidders' valuations. One possible source of such dependence in our context is unobserved heterogeneity in the characteristics of the auctions. While waste plastic is a relatively simple product compared to many other products, there is still a concern that the

Year	2004	2005	2006	2007	2008	2009
Dirty Plastic (measured by recycler)	1.68	1.37	2.42	–	–	–
Dirty Plastic (measured by auctioneer)	–	–	8.50	4.05	3.76	3.32
PET resin (measured by recycler)	0.92	0.77	0.61	–	–	–
PET resin (measured by auctioneer)	–	–	1.28	0.50	0.31	0.28
Not container (measured by recycler)	1.45	1.25	1.24	–	–	–
Not container (measured by auctioneer)	–	–	2.71	1.56	1.32	0.99
Not plastic (measured by recycler)	0.67	0.53	0.40	–	–	–
Not plastic (measured by auctioneer)	–	–	0.67	0.35	0.28	0.25
Other Irregular (measured by recycler)	0.32	0.56	1.84	–	–	–
Other Irregular (measured by auctioneer)	–	–	3.30	1.94	1.70	1.43

Table 10: Average Impurities by Year.

quality measure used to evaluate plastic does not capture quality very well. In order to address this issue, we experimented with other measures of quality.

In addition to the data on quality that we have been using until now, we have information regarding the composition of the impurities contained in the plastic bales. Table 10 shows the breakdown of the impurities by different categories. The sum of the impurities equals 100 minus the quality measure that we have been using. Note that one of the categories listed in the table is $Not\ Container$. This is because plastic products other than containers, such as plastic toys, often have parts made of wood or of metal which make them unsuitable for recycling. Table 11 shows the results from regressing the winning bid on the percentage of different types of impurities. The first column corresponds to the results that we obtained when we use the full set of municipalities for 2008 and 2009 and the subset of municipalities for 2007 which were inspected by the auctioneer in the previous year. The second column corresponds to the results that we obtain using the sample of municipalities that were inspected by the recyclers in 2004 and 2005. Note that the coefficients on each type of impurities is negative except one (Not Container, in the first column). We were unable to reject the null that the coefficients on each type of impurities are equal. The percent of impurities are also highly correlated with each other (as high as about 40%). Given these facts, it is unlikely that the composition of impurities has any significant effect on the values of the bidders once we condition on the quality measure that we use. We feel that the measure of quality that we use does a reasonable job of capturing the true measure of quality.

Next we discuss the private values assumption. The assumption of private values is equivalent to the assumption that knowing the valuations of other bidders does not change ones's own valuation.

Winning Bid	(1)	(2)
Dirty Plastic (Lag)	-133.05^{**}	-62.62
	(48.75)	(285.37)
PET Resin (Lag)	-70.43	-461.22
	(310.75)	(454.38)
Not Plastic (Lag)	-253.50	-754.27
	(551.36)	(663.22)
Not Container (Lag)	276.38	-200.49
	(198.65)	(351.92)
Other Impurities (Lag)	-35.62	-232.88
	(117.08)	(809.41)
Quantity	1.076	-5.54
	(1.94)	(8.66)
Preferred	-30682.09	-35519.80
	(741.34)	(3989.84)
Dist. winning bidder	-7.86^{**}	-6.26
	(3.01)	(7.58)
# MR <50km	586.72	1142.09
	(630.87)	(1284.91)
# CR <50km	-581.17	2056.00
	(1568.02)	(7593.23)
FE	Yes	Yes
Year Dummy	Yes	Yes
Type of Recycler	Yes	Yes
N	430	268

Table 11: Regression of the Winning Bid on Various measures of Impurities and Other Auction and Bidder Characteristics. Includes Municipality FE and Year Dummies. The Winning Bid is Yen/Ton.

One possible way in which private values can break down is if some recyclers have private information regarding the realization of the quality of plastic bales supplied by the municipalities. As we saw in 7 however, the effect of current year quality, q_t, on the winning bid, p_t, is small and not statistically significant. This is consistent with our maintained assumption that the bidders do not have private information concerning the quality of plastic in the coming year. We also looked for evidence that the winner of the auction from the previous year may have private information regarding the current year quality q_t. However, we did not find any positive effect of having the same winner in consecutive years on quality.

Lastly, we discuss some issues related to treating each auction as independent. Recall that all of the recycling auctions are held simultaneously and that most bidders take part in multiple auctions. In the model, we have implicitly assumed that the payoffs from each auction enters lineally in the utility function of the bidders. If this is the case, we can treat each auction in isolation, because maximizing overall utility for the bidder is the same as maximizing utility from each of the auctions. We discuss some of the potential problems with this assumption below.

First, as we saw in 7, the distance between the location of the municipality and the location of the bidder affects valuations. Hence municipalities that are close to each other may induce complementarity from the perspective of the bidder. This may be true to some extent, but unlike school milk delivery for example, the bidder does not have to send a truck to each municipality every day. If two municipalities are located on opposite directions, the bidder may send a truck to one municipality on even days and to another municipality on odd days. The fact that the bidder can time its pickup would make issues associated with topography less important. Indeed, when we look at the geographical dispersion of the municipalities corresponding to the auctions won by a given recycler, it is not the case that all of the municipalities are clustered in one direction.

Second, there may be capacity constraints or returns to scale which may invalidate the assumption that the payoffs from each auction enters linearly in the bidders' utility function. It is worth noting, however, that for many recyclers, the waste plastic that they acquire through the recycling auctions is only a fraction of the total intake of plastic. Indeed, one of the registration requirements for new participants is that it must have had at least one year of prior experience recycling plastic outside the municipal plastic auctions. An important source of waste plastic that is not sold by the auctions that we study include industrial waste plastic. In terms of the overall amount of waste plastic that is recycled, the amount of industrial waste plastic comprise a larger fraction than household plastic. To the extent that the plastic acquired through the auctions does not comprise a large proportion of the overall amount of plastic that the recyclers process, capacity constrains and economies of scale may not be very important. Furthermore, we tried including quantity in the regressions that we ran in the Preliminary Analysis Section. We found that quantity has almost no effect on the winning bid. This is also consistent with our assumption.

Lastly, we note that while we treat each auction in isolation, we can still allow for correlation in the valuation of a given bidder across auctions. That is, conditional on recycler and auction characteristics, the valuation of the bidder may still be correlated across auctions. This would be natural if the source of private values is the costs of operating the recycling plant or the contracts that recyclers have with the users of recycled material. Under fairly weak conditions, the dependence between the auctions disappears exponentially, satisfying the $\alpha-$mixing condition. We can use standard methods to obtain consistent standard errors.[23]

4 Identification

The identification of the bidders' valuations when only the transaction price is observed was first considered in Athey and Haile (2002) for the case of no reservation values, and then in Athey and Haile (2007), for the case of known reservation values. The positive results they obtain regarding the identification of the bidders' bid distributions above the reservation value holds for our model. However, their result on the identifiability of the bidder's valuation does not go through in our setup, since they consider the situation in which the reserve price is known to the bidders ex-ante, while the reserve price in our auction is unknown to the bidders at the time the bids are submitted.

First, it is worth noting that if we could estimate the distribution of the reserve price, R_t, then it is possible to identify the distribution of U_{ij}, using the technique pioneered by Guerre Perrigne and Vuong (2000). What precludes us from directly estimating the distribution of R_t is the fact that R_t is set equal to the same amount for all municipalities in a given year t. What we do instead is exploit the variation in the characteristics of the auctions and bidders.

Note from the previous section that

$$U_{ij} = b_{ij} + \frac{1}{\frac{\frac{\partial}{\partial b}\Pr(b \geq R_t)}{\Pr(b \geq R_t)} + \frac{g_{ij}(b_{ij}|\Xi)}{G_{ij}(b_{ij}|\Xi)}},$$

which implies

$$\begin{aligned} \Pr(U_{ij} \quad &\leq \quad s) = F_{b_{ij}}(\xi^{-1}(s|\Xi)|\Xi). \\ &\text{where } \xi(s|\Xi) = s + \frac{1}{\frac{\frac{\partial}{\partial b}\Pr(s \geq R_t)}{\Pr(s \geq R_t)} + \frac{g_{ij}(s|\Xi)}{G_{ij}(s|\Xi)}} \end{aligned}$$

where Ξ denotes auction and bidder characteristics. If the function $\frac{\frac{\partial}{\partial b}\Pr(s \geq R_t)}{\Pr(s \geq R_t)}$ were known, $\Pr(U_{ij} \leq s)$ is nonparametrically identified, as the functions $F_{b_{ij}}(\cdot|\Xi)$ and $\xi^{-1}(s|\Xi)$ are both identified from the data. Hence the problem of identification reduces to the identification of $\frac{\frac{\partial}{\partial b}\Pr(s \geq R_t)}{\Pr(s \geq R_t)}$. For this problem, we use the restriction that variation in Ξ, such as the number of potential bidders, or the characteristics of bidders other than bidder i, induce variation in $F_{b_{ij}}(\cdot|\Xi)$ and $\xi^{-1}(s|\Xi)$, but it

[23] Similar issues come up in Jia (2008), for example, where there are spacial correlation between observations.

should not change the left hand side.[24] The distribution of values for bidder j should be independent of the number of bidders or the characteristics of other bidders. The function $\frac{\frac{\partial}{\partial b}\Pr(b \geq R_t)}{\Pr(b \geq R_t)}$ is identified by the restriction that changes in Ξ do not induce changes in $F_{b_{ij}}(\xi^{-1}(s|\Xi)|\Xi)$.

Finally, we briefly discuss the identification of the utility function $U(q_t)$ and the cost function $C(q_t)$ of the municipalities. The identification of U and C come from the restriction that the marginal return from increasing quality is equal to the marginal cost from increasing quality, at the levels of quality chosen by the municipalities. Recall that incentives that were introduced in 2008 changed the benefits of increasing quality. Under the maintained assumption that the cost function is constant throughout, the improvement in the quality of the plastic before and after 2008 identifies C, relative to U. As for separately identifying C from U, we use the demographic characteristics of municipalities. Some demographic characteristics, such as the population density, would be an important cost shifter, but we feel that it can be safely excluded from U. It would be more costly for sparsely populated municipalities to increase the number of days to send out trucks to collect different types of recyclable material than densely populated municipalities, for example. However, there is no reason to expect the U to be a function of the population density.

5 Specification and Estimation

5.1 Number of Potential Bidders

In the data set that we work with, we can identify the set of all recyclers who are eligible to bid because the auctioneer requires all recyclers to register prior to the auction. For a given auction, however, this is not the relevant set of potential bidders. Although we do not have data on the number of submitted bids for each auction, the auctioneer communicated to us informally that it is a lot less than the total number of eligible bidders. The distance between the recycler and the municipality is an important cost factor and many recyclers bid in near-by municipalities only. Indeed, in about 90% of the cases, the winning material recycler is located within 200 km of the municipality and the winning chemical recycler is located within 450 km. Given this fact, we opted to treat a recycler as a potential bidder if the distance between the recycler and the municipality is

[24] Exogenous variation of this kind has been used to test the private values model against the common values model, for example in Athey and Haile (2002), and in Haile Hong and Shum (2003). It has also been used to estimate risk aversion, see Bajari and Hortacsu (2005) and Guerre, Perrigne, and Vuong (2009).

less than 200 km for material recyclers and less than 450 km for chemical recyclers.[25]

Since the actual submission of bids is almost costless, the plausible reason for why bidders that are located far away do not submit bids is signal acquisition costs.[26] If the cost of acquiring a signal is fixed for bidders, then the union of the set of winning bidders across auctions with similar characteristics will eventually identify the set of potential bidders for those auctions.[27] While our specification of potential bidders is not perfect, our decision to form the set of potential bidders using the information about the set of actual winners of the auctions can be justified on these grounds. The number of potential bidders as defined above is 12.47 for preferred bidders and 8.00 for non-preferred bidders.

5.2 Law of Motion for q_t

Our estimation proceeds by first estimating $E[q_t|q_{t-1}, e_t]$, and $F_{q_t}(\cdot|e_t, q_{t-1})$, the conditional expectation of q_t, and the conditional distribution of q_t given e_t and q_{t-1}. In order to do so, we begin by specifying the evolution of quality as

$$q_t = H(\alpha q_{t-1} + e_t + \varepsilon_t). \ \varepsilon_t \sim N(0, \sigma^2),$$

where we take $H(\cdot)$ as the distribution function of the standard Normal. Note that

$$E[H^{-1}(q_t)|\Omega_t] = \alpha q_{t-1} + e_t,$$

as e_t is measurable with respect to Ω_t, the information set of the municipality at time t when it chooses its level of effort, e_t. We estimate $E[H^{-1}(q_t)|\Omega_t]$ and σ^2 where $E[H^{-1}(q_t)|\Omega_t]$ is non-parametrically estimated using polynomial sieves of Ω_t. This is enough to recover $E[q_t|q_{t=1}, e_t]$ and $F_{q_t}(\cdot|e_t, q_{t-1})$ because these are simple functions of $E[H^{-1}(q_t)|\Omega_t]$ and σ^2:

$$E[q_t|q_{t=1}, e_t] = E_\varepsilon[H\left(E[H^{-1}(q_t)|\Omega_t] + \varepsilon_t\right)]$$

[25] When the winning bidder was not within the radius we chose, we opted to treat the set of potential bidders as all recyclers within the radius plus the winning bidder.

[26] For example, often recyclers contract out tranportation to a third party, and it may be costly to find out the exact amount that the recycler needs to pay for transportation.

[27] This was pointed out by Gurre, Perrigne, and Vuong (2000). Note that our argument implicitly assumes that there exists high enough realizations of signals such that the probability of winning conditional on acquiring signals is strictly above zero (i.e. the submitted bid is above the reserve price).

and

$$F_{q_t}(s|e_t, q_{t-1}) = \Pr(q_t \leq s|q_{t-1}, e_t) = \Pr(\varepsilon_t \leq H^{-1}(s) - \alpha q_{t-1} - e_t|q_{t-1}, e_t]) = \Phi\left(\sigma^{-1}(H^{-1}(s) - E[H^{-1}(q_t))|\Omega_t]\right).$$

5.3 Bid distribution

We specify the log bids as a three parameter Weibull distribution. Recall from the previous section on identification that the bid distribution is identified above the reserve price, R_t. We let (α, β, γ) be the parameters of the Weibull distribution where γ is the location parameter and α and β are the scaling and the shape parameters. We let (α, β, γ) be (time dependent) parametric functions of observed bidder characteristics such as the type of bidder (preferred material, coax, non-preferred material,...etc.), the distance between the bidders to the municipality and other auction characteristics such as the expected realization of quality, $q^e = E[q_t|\Omega_t]$, which we estimate using sieves of Ω_t as we described above. The conditional density of the bid of bidder i in auction j, b_{ij}, at s $(s \geq R_t)$ is then

$$f_{ij}(s|s \geq R_t) = \frac{1}{(s - \gamma_{ij})} \frac{\beta_{ij}}{\alpha_{ij}} \left(\frac{\log(s - \gamma_{ij})}{\alpha_{ij}}\right)^{\beta_{ij}-1} \exp\left(-\left(\frac{\log(s - \gamma_{ij})}{\alpha_{ij}}\right)^{\beta_{ij}}\right),$$

where $(\alpha_{ij}, \beta_{ij}, \gamma_{ij})$ are the values of the function (α, β, γ) evaluated at the auction and bidder characteristics. Note that if we let F_{ij} denote the CDF of b_i, the probability that the auction will end in the first stage is given by $1 - \prod_i F_{ij}(R_t)$, and the CDF of the winning bid conditional on the event that the auction ends in the first stage is given by

$$F_j(s) = \frac{\prod_i F_{ij}(s) - \prod_i F_{ij}(R_t)}{1 - \prod_i F_{ij}(R_t)} \text{ (for } s \geq R_t)$$

The second stage bid distribution is analogous. Note that for each parameteric function for (α, β, γ) induces a likelihood on the outcome of the auction, which include the winning bid and the identity of the winner. The parameters are estimated using maximum likelihood.

5.4 Bidder Valuations

Recall that bidder valuation and bidding is related through the following first-order condition,

$$U_{ij} = b_{ij} + \frac{1}{\frac{\frac{\partial}{\partial b}\Pr(b \geq R_t)}{\Pr(b \geq R_t)} + \frac{g_{ij}(b_{ij}|\Xi)}{G_{ij}(b_{ij}|\Xi)}}.$$

where G_{ij} is the distribution of the highest bid among bidder i's rivals, g is its pdf, and Ξ denotes auction and bidder characteristics. Hence the CDF of U_{ij}, $F_U(s)$, is given by

$$\begin{aligned} F_U(s) &= \Pr(U \leq s) = \Pr\left(b + \frac{1}{\frac{\frac{\partial}{\partial b}\Pr(b \geq R_t)}{\Pr(b \geq R_t)} + \frac{g_{ij}(b_{ij}|\Xi)}{G_{ij}(b_{ij}|\Xi)}} \leq t \right) \\ &= \Pr(b \leq \xi^{-1}(s)) \end{aligned}$$

where ξ^{-1} is the inverse function of $\xi(b) = b + \frac{1}{\frac{\frac{\partial}{\partial b}\Pr(b \geq R_t)}{\Pr(b \geq R_t)} + \frac{g_{ij}(b_{ij}|\Xi)}{G_{ij}(b_{ij}|\Xi)}}$. Recall that G_{ij} and g_{ij} can be estimated above R_t as we described above. As for the distribution of R_t, we impose a Normal distribution with mean μ_{Rt} and standard error σ_R. The parameters of this distribution are estimated by the restriction that F_U is invariant to the number of bidders and the characteristics of other bidders.

Once we have estimates of G_{ij}, g_{ij} and the distribution of R_t, we can recover the distribution of bidder valuation, $F_U(s)$, above $s = \xi(R_t)$. While we do not require knowledge of F_U below $\xi(R_t)$ for the estimation of the municipality's cost function nor for some of our counterfactual results, we do require knowledge of the whole distribution for some of our counterfactuals. The truncation imposed by the reserve price is less of a problem for auctions with high expected quality, q^e, where the bid distribution is mostly above the reserve price. However, for auctions with low q^e, there is a substantial probablity mass below R_t. When we need the whole distribution of bids, we extrapolate the bid distribution below the truncation point: We do so by fitting a Normal density continuously.

5.5 Municipality

Recall from the model section that,

$$E\left[D_{1t}(q_t, q_{t-1}) - \frac{\partial}{\partial e_t}C(e_t) + \beta\alpha \frac{\partial}{\partial e_{t+1}}C(e_{t+1})\phi(\Phi^{-1}(q_t)) \middle| \Omega_t \right] = 0 \qquad t \leq 2006$$

$$E\left[\begin{array}{c} D_{1t}(q_t, q_{t-1}) - \frac{\partial}{\partial e_t}C(e_t) + \beta\alpha \frac{\partial}{\partial e_{t+1}}C(e_{t+1})\phi(\Phi^{-1}(q_t))\cdot \\ \left(-B_{t+1}1_{\{q_t \in [88,93]\}} f_{q_{t+1}}(q_t+2)\phi(\Phi^{-1}(q_t+2))\right) \end{array} \middle| \Omega_t \right] = 0 \qquad t \geq 2007, \quad (1)$$

where we have replaced H with Φ and H' with ϕ. This equation is simply the first order condition that equates the marginal cost of effort with the marginal expected benefit of increasing quality. This equation will form the basis of our estimation which are based on moment conditions. For this purpose, we first specify the cost of exerting effort as a quadratic function, as $C(e_t) = ce_t^2$ and the non-pecuniary utility from quality as $U(q_t) = \theta q_t$.

Let us define $\tilde{D}_{1t}(q_t, q_{t-1})$ by replacing $E[U'(q_t)\phi(\Phi^{-1}(q_t))]$ with $U'(q_t)\phi(\Phi^{-1}(q_t))$ in $D_{1t}(q_t, q_{t-1})$, writing:

$$\begin{aligned}
&\tilde{D}_{1t}(q_t, q_{t-1}) \\
&= \begin{cases}
B_t f_{q_t}(95) \cdot \phi(\Phi^{-1}(95)) + U'(q_t)\phi(\Phi^{-1}(q_t)) + E[r_t'(q_t)\phi(\Phi^{-1}(q_t))] \text{ if } q_{t-1} \geq 93 \\
B_t f_{q_t}(q_{t-1}+2) \cdot \phi(\Phi^{-1}(q_{t-1}+2)) + U'(q_t)\phi(\Phi^{-1}(q_t)) + E[r_t'(q_t)\phi(\Phi^{-1}(q_t))] \\
\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad \text{if } 88 \leq q_{t-1} \leq 93 \\
B_t f_{q_t}(90) \cdot \phi(\Phi^{-1}(90)) + U'(q_t)\phi(\Phi^{-1}(q_t)) + E[r_t'(q_t)\phi(\Phi^{-1}(q_t))] \text{ if } q_{t-1} \leq 88
\end{cases}
\end{aligned}$$

this function can now be evaluated given parameters. This is because f_{q_r} can be derived from knowledge of F_{q_t}, which we have estimated, and $r_t(\cdot)$ can be derived once we know the bidder's bid distribution. Now note that the derivative of the cost function in equation 1 is additive in ε once we substitute out the unobservable effort e_t and e_{t+1}: $\frac{\partial}{\partial e_t}C(e_t)$ is equal to $2c\cdot(\Phi^{-1}(q_t) - \alpha q_{t-1} - \varepsilon_t)$, for example. We then exploit the orthogonality between $X_{mt} = \tilde{D}_{1t}(q_t, q_{t-1}) - 2c \cdot (\Phi^{-1}(q_t) - \alpha q_{t-1}) + 2\beta\alpha c\cdot(H^{-1}(q_{t+1}) - \alpha q_t)\phi(\Phi^{-1}(q_t))$ and Ω_t for $t = 2005, 2006$ and $X_{mt} = \tilde{D}_{1t}(q_t, q_{t-1}) - 2c\cdot(\Phi^{-1}(q_t) - \alpha q_{t-1}) + 2\alpha\beta c \cdot (\Phi^{-1}(q_{t+1}) - \alpha q_t)\phi(\Phi^{-1}(q_t)) \left(-B_{t+1}1_{\{q_t\in[88,93]\}} f_{q_{t+1}}(q_t+2)\phi(\Phi^{-1}(q_t+2))\right)$ and Ω_t for $t = 2007$.[28] Ω_t includes all auction and bidder characteristics known at time t, such as q_{t-1}, the number of potential material bidders, chemical bidders, size of the bidders and so on. Note how the unobservable variable e_t has been substituted out of the expression estimating equation so that the moment conditions are functions of only observables and parameters. Hence if we let Z_{mt} denote variables that are in Ω_t and orthogonal to X_{mt}, we can form our GMM criterion function as

$$Q = X'Z(Z'Z)^{-1}Z'X.$$

where X is a $(MT \times 1)$ vector of X_{mt} and Z is a $(MT \times K)$ matrix of instruments Z_{mt}, where M

[28] Note that we cannot form moment conditions for $t = 2008$ because that would require quality data for 2009, or q_{2009}.

is the number of municipalities, T is the number of periods and K is the size of the vector Z_{mt}.

5.6 Value of Material Recycling

Lastly, for some of our counterfactuals, we need to estimate the social benefit of material recycling over chemical recycling. Recall that the rationale for giving preferential treatment to material recyclers over chemical recyclers is that material recycling is considered more environmentally friendly. Given that the reserve price plays a key role in determining the fraction of auctions won by material recyclers and chemical recyclers, we estimate the relative social benefit of material recycling by assuming that the reserve price is set each period to maximize social benefit.[29] In particular, the reserve price R_t solves

$$\max_{R_t} E\left[\sum_{m=1}^{M} 1_{\{MR_m\}} \cdot (U_{MR_m} + V_t^M) + 1_{\{CR_m\}} \cdot U_{CR_m}\right]$$

where $1_{\{MR\}}$ is an indicator function for the event that a material recycler wins the auction: $\{MR_m\} = \{\max_{i \in N_P} b_{im} \geq R_t\}$ and $1_{\{CR\}}$ is defined analogously. V_t^M is the relative social benefit of having material recycler win, U_{MR_m} is defined as the highest bidder valuation among the material bidders for auction m and U_{CR_m} is defined as the highest bidder valuation among chemical recyclers.[30] V_t^M is estimated so that the realized reserve price satisfies

$$\frac{\delta}{\delta R_t} E\left[\sum_{m=1}^{M} 1_{\{MR_m\}} \cdot (U_{MR_m} + V_t^M) + 1_{\{CR_m\}} \cdot U_{CR_m}\right] = 0.$$

5.7 Implementation

Our estimatior is a semi-parametric sieve M-estimator with dependent data where the dependence across observations arises due to the fact that one bidder participates in multiple auctions.[31] In particular, our estimation can be viewed as a $2-$step procedure where the the first stage conditional expectation is estimated using polynomial sieves and the second stage finite dimensional parameters are obtained as plug-in estimator. More formally, if we let our parameters be denoted as (θ, h) where

[29] The restriction that the reserve price is optimally set is required only to estimate the social benefit of material recycling. Estimates of other parameters of the model do not depend on this restriction.

[30] We assume that the auctioneer values material recyclers who had their preferential treatment revoked in the same way they value chemical recyclers.

[31] One can view our estimator as a minimum distance estimator by observing that the sieve MLE estimator is numerically equivalent to a least squares estimator in our context.

h is the conditional mean function and θ is the finite dimensional parameters, our estimator $\hat{\theta}$ solves

$$Q_N = \sum_{t=2005}^{2009} \frac{1}{M} \sum_{i=1}^{M} l_t(Z_i, h) + \left\| \sum_{t=2005}^{2009} \frac{1}{M} \sum_{i=1}^{M} m_t(Z_i, h, \theta) \right\|^2 \text{ with } \min_{\theta} \left\| \sum_{t=2005}^{2009} \frac{1}{M} \sum_{i=1}^{M} m_t(Z_i, \tilde{h}, \theta) \right\|^2 = 0 \text{ for all } \tilde{h}.$$

where l corresponds to the log likelihood of the sieve MLE and m correponds to the stacked moment conditions.[32]

Ackerberg, Chen and Hahn consider the same criterion function as above in one of their examples and shows the asymptotic normality of θ. More generally, Chen Linton, van Keilegom (2003) shows $\sqrt{M}-$ asymptotic normality of finite dimensional parameters which minimize a criterion function that depends on an initial nonparametric estimate with dependent data. Taken together with the results of Chen and Shen (1998) where they derive the asymptotic normality of smooth functionals of sieve estimates under $\beta-$mixing,[33] the parametric component of the two step estimator is $\sqrt{M}-$ asymptotic normal.

The mixing condition that is required for the asymptotic normality result is a restriction on the rate at which dependence in the data vanishes. In our context, bidders participate only in auctions within a given radius. This ensures that auctions that occur far apart are independent. Under some assumptions on the data generating process, our data satisfies $\beta-$mixing.[34]

In what follows we directly bootstrap the estimator to obtain estimates of the standard errors. Application of the bootstrap in semi-parametric settings with dependent data include Chen and Conley (2001) and Chen and Ludvigson (2009).

[32] Note that the sieve MLE is independent of σ, the standard error of ε in the transition function of q. Hence it is possible to treat $\hat{h}$ as a non-parametric sieve MLE and $\hat{\sigma}$ as a plug-in estimate. Note also that we can write a parametric M-estimator as a method of moments estimator by using the first-order condition. Hence it is possible to write our estimator as solving a criterion function of the form given in the text. The restriction that $\min_\theta \left\| \sum_t \frac{1}{N} \sum_{i=1}^{N} m_t(Z_i, \tilde{h}, \theta) \right\|^2 = 0$ for all $\tilde{h}$ is not necessary, but this condition allows us to remain in the framework of a 2-step procedure while allowing us to estimate the finite dimensional parameters sequentially. One drawback of this assumption is that we need to take linear combinations of overidentified moment restrictions in the GMM.

[33] Let $\mathcal{M}_t^{t+\tau}$ denote the σ-algebra generated by $\{Z_s\}_{s=t}^{t+\tau}$. Define $\beta(\tau) = \sup_t \sup_{A \in \mathcal{M}_{t+\tau}^{\infty}, B \in \mathcal{M}_{-\infty}^{t}} |E[A|B] - E[A]|$. $\{Z_s\}$ is said to be $\beta-$mixing if $\beta_\tau \to 0$ as $\tau \to \infty$.

[34] Consider, for example, a DGP where municipalities and bidders are (randomly) located on lattices and the sample region expands in one dimension. A unit of observation is a stacked vector of characteristics of the municipality and the bidders within a specified distance. Our observations would then satisfy $\beta-$mixing. For a more general DGP for spatially correlated observations, see for example Conley (1999). For an empirical application with geographical dependence, see, for example, Jia (2008).

6 Results

6.1 Estimation of $E[q_t|q_{t-1}, e_t]$ and F_{q_t}

Recall that our first step in the estimation involved estimating the conditional expectation of q_t and the conditional distribution of q_t given q_{t-1} and e_t. This required us to estimate $E[H^{-1}(q_t)|\Omega_t]$. We estimated this function with polynomial sieves of Ω_t using nonparametric MLE. We included the first and second polynomial terms of q_{t-1}, the number of preferred and non-preferred potential bidders, N^P, and N^{NP}, the distance between the municipality and the potential bidders as well as a dummy for waste management unions. Moreover, we included a dummy variable in the sieve for $t = 2007$ and $t = 2008$ to account for the fact that q_t and q_{t-1} was measured by the auctioneer for only a subset of the municipalities. The coefficients on all of the variables were allowed to be different for each year. The exact specification is provided in the Appendix. In Figure 4, we present the distribution of q_t given Ω_t, for $q_{t-1} = 80$, 90, and 99. The red lines correspond to $q_{t-1} = 80$, the blue lines to $q_{t-1} = 90$, and the black to $q_{t-1} = 99$. The top panel is for $t = 2007$, one year before the introduction of the incentive schemes,[35] and the bottom panel is for $t = 2009$, the second year of the incentive scheme. Except for q_t, Ω_t was otherwise set equal to the average over the whole sample period. Note that the distribution shifts to the right as q_t increases, and also that the distribution shifts considerably to the right in 2009.

6.2 Estimation of the Bid Distribution

We parameterized the log bids as a Weibull distribution with a location parameter. We specified the shape, scale, and the location parameters as linear functions of auction and bidder characteristics. In particular, we included year dummies and the expected quality, q_t^e, computed from the previous step. We allowed the coefficient on q_t^e to depend on whether the quality of the municipality was measured by the auctioneer or by the winning bidder. Figure 5 shows the estimated bid distribution for material recyclers (top panel) and for chemical recyclers (bottom panel).[36] The three curves correspond to the bid distribution for $q_t^e = 80$, 90, and 99, respectively. For material recyclers as well as chemical recyclers, the distribution shifts to the right as we increase q_t^e, but the bid

[35] The distribution in the top panel was created using the coefficients estimated for municipalities that were inspected by the auctioneer in 2006 so as to be comparable with the lower panel.

[36] Except for the measure of plastic quality which we vary, the characteristics of the auction and the bidders are set to sample average.

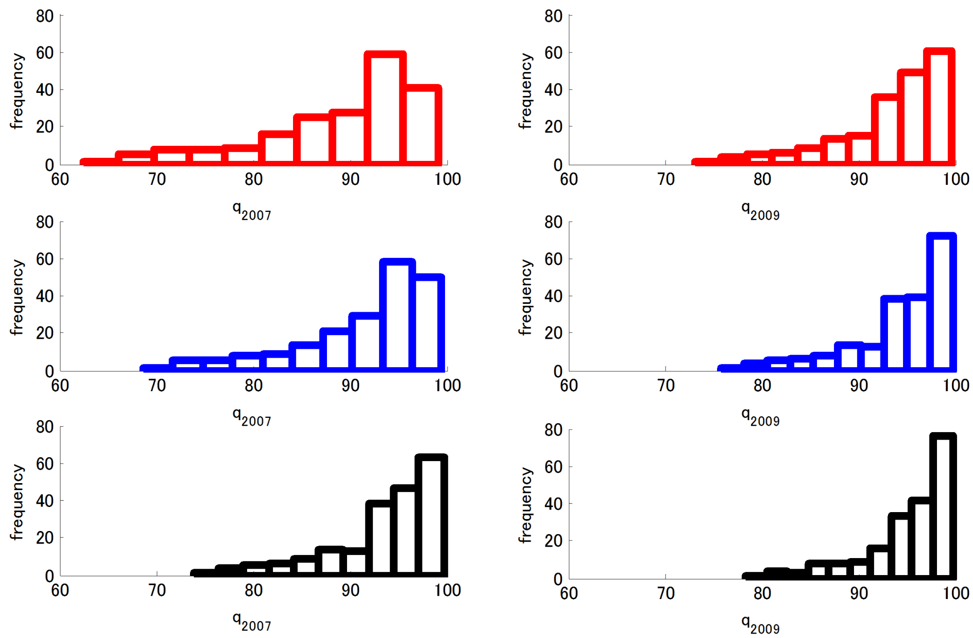

Figure 4: Conditional distribution of q_t Given q_{t-1}. The left three panels correspond to $t = 2007$, one year before the introduction of the incentive scheme. The three right panel corresponds to $t = 2009$, the second year of the incentive scheme. The top panels correspond to $q_{t-1} = 80$, the middle to $q_{t-1} = 90$, and the bottom to $q_{t-1} = 99$.

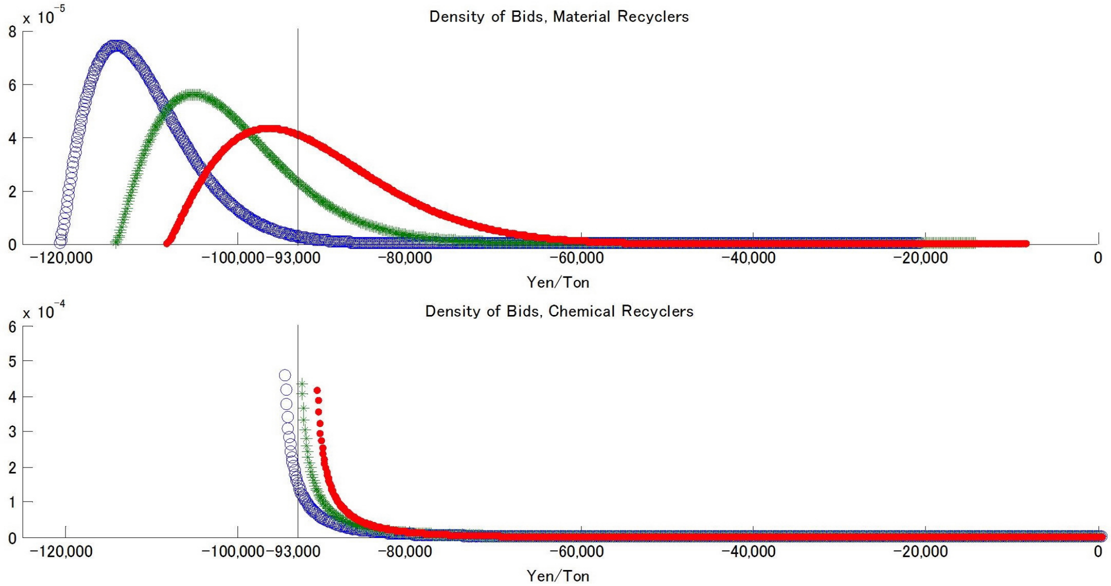

Figure 5: The Density of Bids, for Material Recyclers (Top Panel) and for Chemical Recyclers (Bottom Panel) for 2009. From the left, the curves correspond to $q_t^e = 80$, $q_t^e = 90$, and $q_t^e = 99$, respectively. Except for the plastic quality and the type of bidder, other characteristics of the auction are set to the sample average. The bottom panel corresponds to the bid distribution for Coax recycling.

distribution of the material recyclers are more sensitive, as we saw in Table 7. The straight line in the figure is drawn in at $-93,000$, the reserve price in 2009.

6.3 Estimation of the Distribution of the Reserve Price and the Value of Material Recycling

Our estimates of the distribution of the reserve price and the value of material recycling is reported in Table 12. We specified the reserve price to be distributed Normal with μ_t and σ and the values of μ and σ are reported in the left column of the Table. The mean of the distribution is failry close to the actual realizations of the reserve price.[37] As for the value of material recycling over chemical recycling, we find that postive values, ranging from the low of around $49,000$ to the high of around $85,000$.

[37] The reserve price was $-165,000$, $-123,000$, $-105,000$, $-97,000$, $-93,000$ for 2005 to 2009.

	Estimates		Estimates
$\mu_{R,2005}$	-18703 (7100)	V_{2005}	67719 (39949)
$\mu_{R,2006}$	-11640 (5112)	V_{2006}	85460 (40790)
$\mu_{R,2007}$	-10499 (7146)	V_{2007}	51762 (16572)
$\mu_{R,2008}$	-87543 (8803)	V_{2008}	48941 (8870)
$\mu_{R,2009}$	-75824 (11128)	V_{2009}	53677 (15762)
σ_R	4875 (3891)		

Table 12: Parameter Estimates of the Distribution of the Reserve Price and the Value of Material Recycling. $\mu_{R,t}$ and σ_R are the mean and standard error of the distribution of the reserve price in year t. V_t is the value of Material recycling over Chemical recycling in year t.

6.4 Estimation of Municipality Cost Function

We present our estimates of the cost function of the municipalities as well as the non-pecuniary utility U, and α in Table 13. Recall that we specified our cost function $C(e_t)$ as $C(e_t) = ce_t^2$ and the non-pecuniary utility from quality as $U(q_t) = \theta q_t$. α is the parameter in the transition equation for q_t. We did not estimate the discount factor, but rather imposed 0.95. First, θ is estimated to be close to zero, and almost negligible compared to the quadratic cost function: We estimated the coefficient of the cost function to be more than $12,000$. This implies that at the average level of quality ($q = 0.92$), it takes about $4,665$ yen to remain at that level. Note that we have estimated α to be greater than one, but this is does not imply that the quality increases over time with zero effort. Recall that $q_t = H(\alpha q_{t-1} + e_t + \varepsilon_t)$, hence if we start with q_{t-1} at 0.95 and want to remain at 0.95, on average, we need effort $e_t = H^{-1}(0.95) - \alpha \cdot 0.95 \approx 1.64 - 1.08 = 0.56$.

We also estimated a conversion rate for the quality measurements taken before 2005, the quality measurements taken by the winning bidder in 2006, and the quality measures taken by the auctioneer since 2006. We assume a parametric form for conversion as

$$q = a_{04,05} \cdot q_\tau (q_\tau + \frac{1}{a_{04,05}} - 1)$$

	Estimates
θ	-2.89
	(3.33)
c	12978.11
	(4131.6)
α	1.136
	(0.548)
$a_{04,05}$	8.07×10^{-5}
	(1.1×10^{-3})
a_{06}	3.55×10^{-4}
	(5.0×10^{-3})

Table 13: Parameter Estimates. θ is the parameter for nonpecuniary payoff for increasing quality, c is the coefficient of the cost function, and α and σ are related to the law of motion for q_t.

and

$$q = a_{06} \cdot q_\tau (q_\tau + \frac{1}{a_{06}} - 1)$$

where the left hand side of the expressions are the implied quality measure by the auctioneer, and $\tau = 2004$, or 2005 in the first expression and $\tau = 2006$ in the second expression. The specification was chose so that $q_\tau = 0$ implies $q = 0$ and $q_\tau = 1$ implies $q = 1$. We report the coefficients in the bottom two rows of Table 13. We estimated the coefficients $a_{04,05}$ and a_{06} to be positive, which implies that the equivalent measure by the auctioneer is always smaller than the measures taken by the winning bidder. However, the relationship is almost linear.

6.5 Estimation of the Effect of the Incentive Scheme

The incentive scheme that was first introduced in 2008 consists of two parts, one that is based on the quality threshold and the other based on the difference between the winning bid and the base price. We mentioned that the second part can actually have negative incentives to increase quality. Figure 6 shows histograms of the marginal benefit that accrues to the municipality from each part of the incentive scheme when effort is increased by one unit for $t = 2009$. The first panel corresponds to the incentive scheme based on the quality threshold. This is positive, and ranges from $1,000$ yen to $2,000$ yen. The second panel corresponds to the part of the incentive scheme based on the difference between the winning bid and the base price. Note that for a significant fraction (about 40%) of the municipalities, the marginal benefit is negative. That is, even though the base price is adjusted to account for the differences in the average winning bid among the different types of recyclers, the

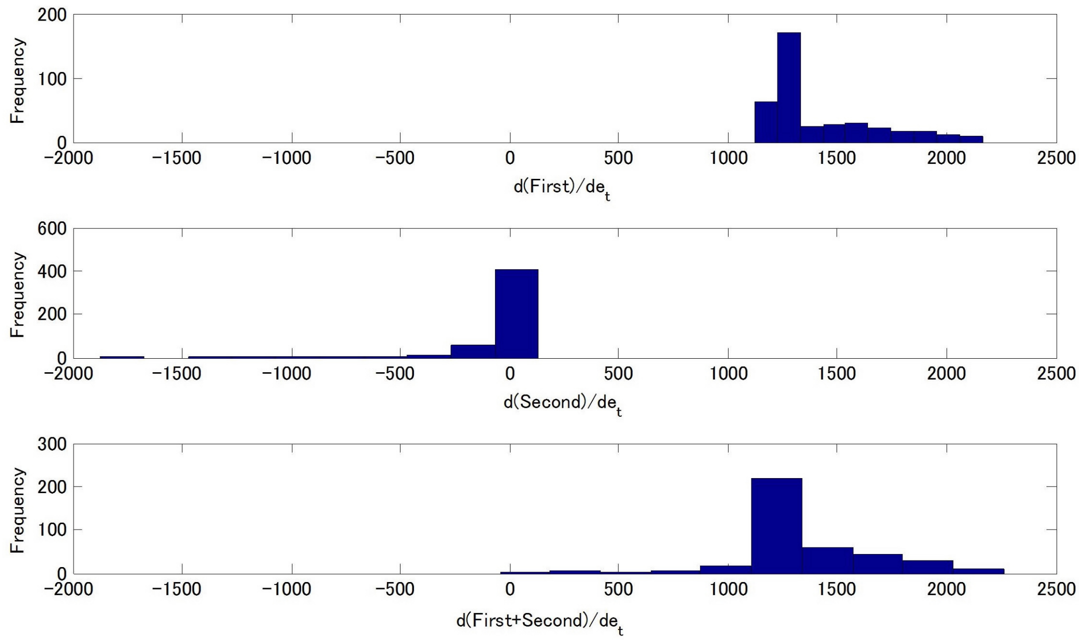

Figure 6: Marginal Benefit of Increasing e_t by One Unit. First Panel Corresponds to the Quality Threshold, and Second Panel Corresponds to the Price Differential. The Third Panel Presents the Sum of the First Two.

base price for the material recyclers are set too high relative to the base price for chemical recyclers to make it worthwhile for municipalities to improve the quality.

The counteracting forces of the incentive scheme can be seen from the bottom panel of Figure 7 as well, which plots the expected payoff from the incentive scheme as a function of the expected quality for a particular municipality. Note that the expected payoff is U-shaped. At lower levels of quality, increasing quality has a negative effect on payoff because the effect from the change in the composition of the winning bidder dominates the direct effect of increasing bids. At higher levels of quality, the winning bidder is a material recycler, and the direct effect starts to dominate the composition effect.

The third panel of Figure 6 displays the net effect of the two parts of the incentive scheme. The third panel shows that while the second part of the incentive scheme is negative for a substantial fraction of the municipalities, the overall effect of the incentive scheme goes in the right direction.

We next explore the welfare implications of inefficient levels of investment.

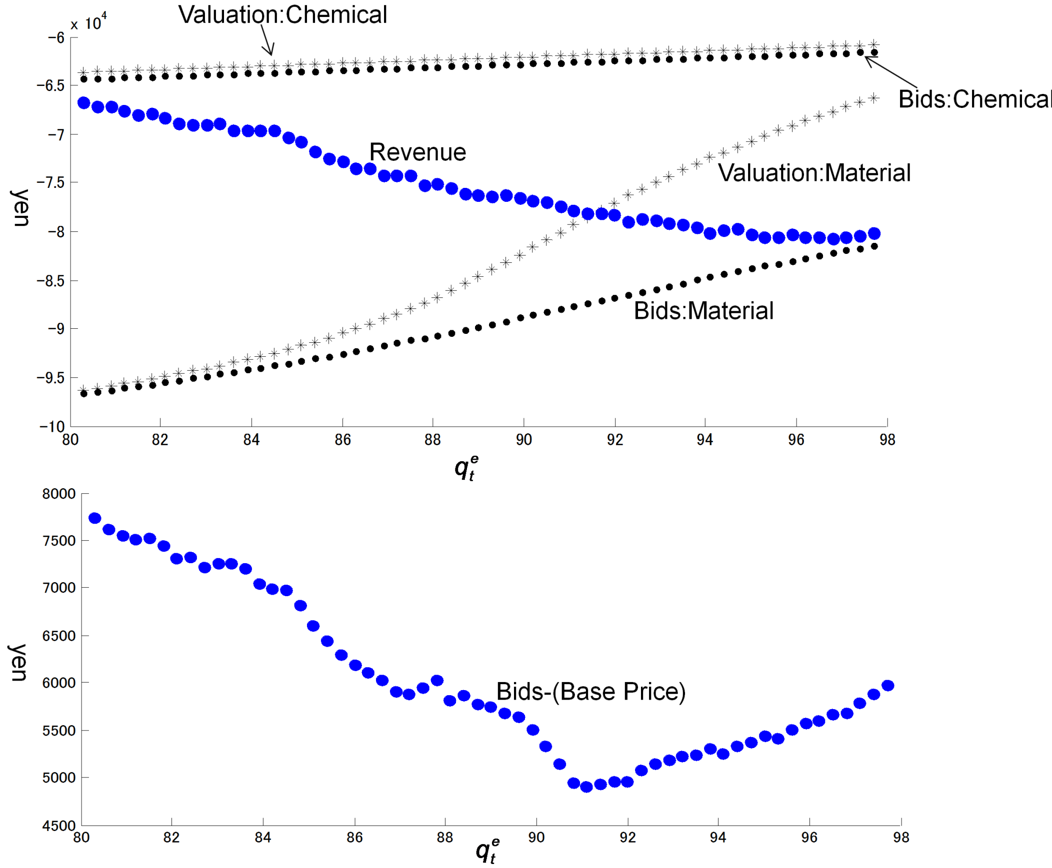

Figure 7: Plot of Expected Maximum of Bidder Valuation, Expected Maximum of Bids and Revenue as a Function of Quality. The curve labeled Revenue in the top panel is the revenue to the municipality in the absence of any incentive scheme. The curve in the bottom panel is the $0.4\times$(Winning Bid-Base Price).

7 Counterfactual Policy Experiments

7.1 Overview

In this section, we consider the first best outcome and compare the performance of various incentive schemes. The first best outcome solves a dynamic programming problem where the period return function is given by the expected maximum of bidder valuations less the cost of investing in quality. Recall that we have estimated the relative social benefit of having material recycling over chemical recycling, V_t^M. Thus, the first best solves

$$\begin{aligned} V_t(q_{t-1}) &= \max_{e_t} E[R_t^{SP}(q_t)] - C(e_t) + \beta E[V_{t+1}(q_t)] \\ s.t.\ q_{t-1} &= H(\alpha q_{t-1} + e_t + \varepsilon_t). \end{aligned}$$

where $R_t^{SP}(q)$ is the maximum of bidder valuations, $R_t^{SP}(q) \equiv \max \left\{ \{U_i(q) + V_t^M\}_{i \in N^P} \cup \{U_i(q)\}_{i \in N^{NP}} \right\}$. Because we only know $\{V_t^M\}$ for $t \in \{2005, ..., 2009\}$, we imposed our estimate of V_{2009}^M for all future values of V_t^M. For our counterfactual policy experiment, we vary the period return function R_t and solve for the policy function of the seller, $e_t(\Omega_t)$. Then given $e_t(\Omega_t)$, we simulate draws from bidder valuations to compute welfare.

7.2 Pre-Policy Change

We first compute the welfare loss from quality distortion when there were no monetary incentives to invest in quality. This corresponds to the situation before the policy change was introducedd in 2008. In the left panel of Figure 8, we plot the welfare loss against the number of potential bidders. The average welfare loss per ton per year is about $20,000$ yen. Without any incentive scheme, the municipalities exert almost no investment in quality.

7.3 Post-Policy Change

We next compute the welfare loss from quality distortion under the current policy with subsidy from quality and price. In the right panel of Figure 8, we plot the welfare loss against the number of potential bidders. The average welfare loss per ton per year is about $11,500$ yen. Notice that the welfare loss declines as the number of potential bidders increases. Notice that under the current policy, the wedge between bidder valuation and bids plays an important role. As the number of

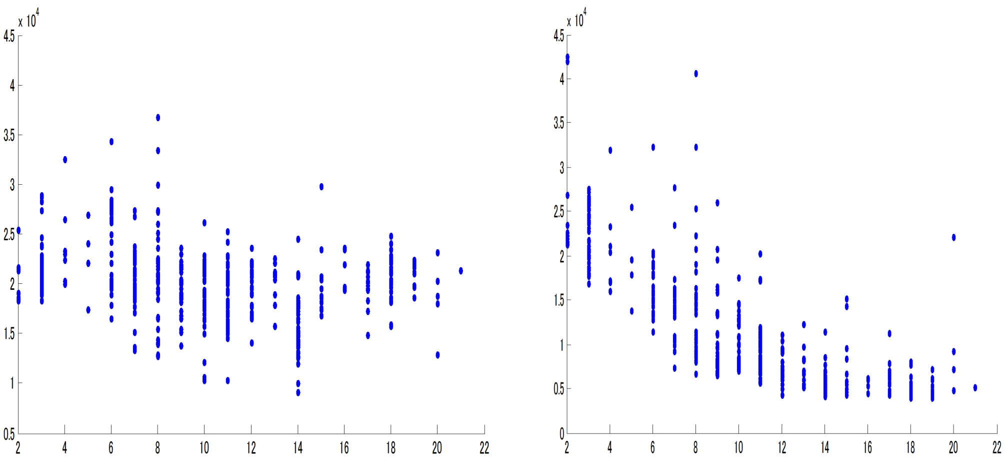

Figure 8: Welfare loss due to quality ditortion as a function of the number of potential bidders. Left panel corresponds to the pre-incentive period, and the right panel corresponds to the post-incentive period.

potential bidders increases, the wedge between the valuations and the bdis decreases. This translates to a decreasing welfare loss as a function of the number of potential bidders.

8 Conclusion

This paper investigated the effects of auction design on the seller's incentives to invest in quality. We showed that standard auctions do not necessarily provide the right amount of incentives for the sellers to invest. In a simple first price auction, for example, the profit maximizing level of quality provided by the sellers is lower than the socially optimal level of quality, and the welfare loss associated with insufficient provision of quality is about $5,200$ yen per ton of plastic, or about 5.6% of the average winning bid.

We also found that the current incentive scheme that is in place is not optimal, and furthermore, provides incentives to decrease, rather than increase, quality in some instances. This is because the auction gives preferential treatment to material recyclers who have higher costs on average, and increasing quality makes it more likely that the material recyclers will win the auction.

An issue that we did not explore in this paper is the welfare impact of changing the composition of plastic that is recycled by the material recyclers and the chemical recyclers. The rationale for giving preferential treatment to material recyclers is that material recycling is environmentally more friendly. A possible extension of the paper may use information about the reserve price that the auctioneer sets to identify the welfare impact of changing the composition of winners. If the reserve price is set to maximize social welfare, it is possible to recover the welfare gains from the use of material recycling instead of chemical recycling. This will allow us to implement an auction that achieves the right composition of winners that use different recycling technology as well as provide the right incentives for municipalities to invest in quality.

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